

THESIS

NEW INSIGHTS INTO PLEISTOCENE HOMININ BUTCHERY AND TOOL CHOICE
FROM A 0.9 MA FOSSIL ASSEMBLAGE FROM THE HEB SITE, OLDUVAI GORGE,
TANZANIA.

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ABSTRACT

NEW INSIGHTS INTO PLEISTOCENE HOMININ BUTCHERY AND TOOL CHOICE FROM A 0.9 MA FOSSIL ASSEMBLAGE FROM THE HEB SITE, OLDUVAI GORGE, TANZANIA.

Cut marks on animal bones have the potential to inform on hominin diet and tool use. Although these important traces of behavior appear as early as 3.4 Million years ago, they normally are rare in fossil assemblages in part due to the exceptional preservation of bone surfaces required to study them. Olduvai Gorge is unique in having many fossil assemblages with well-preserved cortical surfaces that allow identification and study of bone surface modifications. Most of these assemblages are from Beds I and II as fossil preservation is generally poor in the younger Beds.

The present study analyzes the well-preserved fossil assemblage recovered from renewed excavations of the HEB site by the Olduvai Gorge Coring Project (OGCP). The HEB site is stratigraphically positioned in lower Bed IV, just above Tuff IVA, dating to ~0.9 Ma and was first excavated by Mary Leakey's team in 1962. These fossils exhibit a large number of cut marks and are in direct association with Acheulean tools; making this site important for inferring the feeding and tool use behavior of *Homo erectus*.

Optical profilometry protocols developed by Pante et al (2017) were used to obtain 3D quantifiable micromorphological measurements of 256 experimentally created cutmarks, and 20 archaeological cutmarks from HEB site Olduvai Gorge. Focusing on the micromorphological

measurements, this study used quadratic discriminant analyses models to classify the archaeological cutmarks from HEB site based on technology and raw materials types of the stone tools used to create those marks. The discriminant models on raw material types only, tool types only and both raw material and tool types had 64.8%, 77.3% and 68.4% classification accuracies respectively. Results from the models indicate that cut marks at HEB were made by using both flakes and biface tools, made from lava and quartzite raw materials. These results are consistent with Leakey (1994) excavations, which showed a significant prevalence of flakes and bifaces made from volcanic lava and quartzite raw materials. When interpreted in conjunction with butchery experiments, this study can help us understand hominin tool use and choices at HEB site, Olduvai Gorge - around 0.9 million years ago.

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CHAPTER 1 INTRODUCTION

1.1 Background and Research problem

Cutmarks on fossilized bone surfaces have been used to establish hominin processing of animal tissue using stone tools during the Pleistocene in Africa (Bunn et al, 1986; Fisher, 1995; Potts & Shipman, 1981). Association of Early Stone Age (ESA) tools with cut marks at many Pleistocene sites, further solidified the butchery utility of these tools (Potts & Shipman, 1981; Semaw et al. 2003). Discovery of early *Homo* remains (Leakey et al. 1964) and further research at these ESA sites has characterized early *Homo* as the actor responsible for butchering animals using ESA tools that they produced (Bunn, 1981; 2001; Bunn et al, 1986; Roche et al. 2006).

Nonetheless, despite the assertion that hominins were using ESA lithic tools for butchery purposes; variability and succession of the ESA technologies from Oldowan (characterized by flake and core tools) to Acheulian (characterized by biface handaxes) raised questions over similarity in function across these lithic industries (technologies) (de la Torre & Mora, 2014; de la Torre, 2016; Galan & Dominguez-Rodrigo, 2014; Toth, 1985). Broader questions on the evolutionary significance of lithic technological variability (flakes and bifaces) during the ESA are being addressed by ongoing research and efforts to understand the transition from the Oldowan to Acheulian (de la Torre et al. 2012; de la Torre et al, 2018).

In addition to the questions on hominin butchery behavior raised from observed technological variability of the ESA, recent lithic and taphonomic studies have also shown that, different representation of raw material type within and across lithic assemblages can be useful in understanding hominin butchery behavior (Blumenschine et al. 2008; Braun et al. 2009; Goldman-

Neuman & Hovers, 2012; Stout et al. 2005). Major hypotheses on raw material-type use and preferences revolve around questions on whether hominins used certain raw materials based on their suitability for knapping (size, shape and material properties), edge functionality (durability, retouch frequency), production efficiency and expediency, cultural differences or their relative accessibility or availability for hominins (distance from butchery sites) (Braun et al. 2009; Key et al. 2020).

Recent taphonomic advances in quantitative classification of cut mark micromorphology (Gonzalez et al. 2015; Keevil, 2018; Keevil et al. 2018; Pante et al. 2017) have presented novel ways of addressing some of these questions. By quantitatively studying variations between micromorphological measurements (width, length, volume, surface area, depth etc.) of cut marks made by varying technologies; researchers now have a means to study the functions of ESA technologies in butchery (Keevil, 2018; Keevil et al. 2018; Machin et al, 2007; Merrit & Peters, 2019). These quantitative methods have also been applied to classify cut marks based on raw material types (Keevil, 2018; Keevil et al. 2018) further offering insights into hominin tool use and choice during butchery, which is significant in understanding hominin behavioral ecology during the Pleistocene (Blumenschine et al. 1994).

The renowned paleoanthropological site Olduvai Gorge, Tanzania, is particularly suited for studies that address hominin butchery behavior from bone surface modifications such as cut marks (Bunn et al. 1986; Shipman, 1986; Potts & Shipman, 1981). Attempts to use cut mark micromorphological measurements to infer hominin tool use during butchery need the availability of large fossil bone assemblages with well-preserved cortical surfaces and these are abundant at Olduvai Gorge (Bunn et al. 1986). Researchers have recorded many potential Pleistocene sites at Olduvai Gorge that have fossil bone assemblages with cut mark traces, and are associated with

ESA artifacts as well as hominin remains (Bunn et al. 1986; Leakey, 1971; Leakey & Roe, 1995; Shipman, 1986; Pante & de la Torre, 2018; Potts & Shipman, 1981). Additional advantages such as reliable radiometric dates, well established stratigraphy, paleoenvironmental markers, and proximity to analogy sources like contemporary hunter gatherer groups (such as the Hadzabe), makes Olduvai Gorge sites suited for zooarchaeological studies of hominin butchery during the Pleistocene (Bunn et al. 1986; Key et al 2020; Shipman, 1986; Uno et al. 2018).

Among important Olduvai Gorge sites, is the HEB site, which was named after Professor Herberer by Lois Leakey. The HEB site is stratigraphically positioned in lower Bed IV, just above Tuff IVA, dating to ~0.9 Ma and was first excavated by Mary Leakey's team in 1962 (Leakey & Roe, 1994). Recently, the site has yielded a well-preserved fossil assemblage recovered from renewed excavations by the Olduvai Gorge Coring Project (OGCP). From the project, 60 fossil bones were diagnosed with 110 cutmarks that are in direct association with Acheulean stone tools, making this site important for inferring the feeding and tool use behavior of *Homo erectus*. Pioneering research at Olduvai Gorge, involving the use of cut marks to infer hominin feeding behavior was largely based on Frida Leakey Korongo (FLK) *Zinjanthropus* site assemblage (Blumenschine, 1995; Blumenschine et al, 2007; Dominguez-Rodrigo & Barba, 2005; Dominguez-Rodrigo & Piquares, 2005; Dominguez-Rodrigo et al, 2010; Dominguez-Rodrigo et al, 2014; Egeland et al, 2004; Pante, 2010; Pante, 2012; Pante et al, 2012, 2013; Pickering & Dominguez-Rodrigo, 2006), and has greatly progressed from simple identification of patterning in the butchering techniques (which is done by analyzing the location and frequency of cut marks on different skeletal parts in conjunction with knowledge of animal anatomy) (Bunn et al. 1986), to inferences on hominin timing and access to carcasses (whether hominins or carnivores had the first or earliest access to a carcass) which implies hunting or scavenging modes of subsistence

(Blumenschine et al. 2007; Dominguez-Rodrigo et al. 2015; Pante et al. 2012; Pante et al. 2015; Parkinson, 2013; 2018).

The analysis of hominin timing and access to carcasses is done by analyzing the overall percentage of cut marks in an assemblage and their positions relative to carnivore tooth marks (Blumenschine, 1995). Resulting frequencies will suggest either passive scavenging (late access to carcasses by hominins – mostly exploiting non-meat products like marrow), aggressive scavenging (late access to carcasses by hominins – accessing both meat and marrow) or hunting (hominins having had primary access to carcasses and the majority of the meat) (Dominguez-Rodrigo & Barba, 2007; Blumenschine et al. 2007; Pante et al, 2012, 2013, 2015). This means that such models relied heavily on accurate identification of mark traces on bone surfaces made by different actors (hominin cut marks versus carnivore tooth marks), a feat that has advanced as researchers have abandoned qualitative descriptions of bone surface modifications (Blumenschine et al. 1988; Blumenschine et al. 1996; Fisher, 1995; Shipman & Rose, 1983), in favor of more quantifiable, replicable and standardized micro-morphometric methods for diagnosing marks made by human actors (cut marks) (Bello & Soligo, 2008; Bello et al. 2009; Boschín & Crezzini, 2012; Courtney et al. 2019; Dominguez-Rodrigo et al, 2009; Otárola-Castillo et al. 2018; Pante et al. 2017)

The use of quantifiable micro-morphometric methods for diagnosing cut marks has proven successful and researchers have further developed these methods to distinctively infer cut marks made by specific tool types (flakes versus hammerstones or simple versus retouched flakes/tools) and even, specific raw materials of the tools used to create such cutmarks (De Juana et al. 2010; Greenfield, 2006; Keevil et al. 2018; Maté-González et al. 2018). These advancements then provided novel ways of investigating dynamic human behaviors, such as using cutmark

measurements to infer hominin choice and use of ESA technology and raw material types during butchery (Keevil, 2018).

Keevil (2018) used high-resolution 3-D laser scanning (optical profilometry) protocols developed by Pante et al (2017), and statistical models (quadratic discriminant analyses) to characterize cut mark micromorphology into classes that distinguish different ESA technologies (flakes or bifaces) and raw material types. Furthermore, Keevil (2018) demonstrated that it was possible to identify such relationships between cut mark morphology and properties of stone tools that created the mark in the fossil record with similar accuracy.

This thesis, therefore, applies Keevil's (2018) model to the analysis of the recently discovered cut marks from the 0.9 Ma HEB site – fossil assemblage. The study uses variations in the micro-morphometric measurements of cutmarks obtained using 3D optical profilometry, to classify cutmark traces into specific technology and raw materials used to create those cutmarks. Experimental cutmark data from Keevil (2018) are used as training dataset to the discriminant statistical models classifying the technology and raw material types of the unknown archaeological cutmarks from HEB site. Results coupled with frequency and distribution of artifacts at the site and actualistic butchery studies, can indicate patterns in which ESA tools were used for butchery based on their technology and raw material types.

1.2 Goal of the study

The main goal of the study is therefore, to investigate *Homo erectus* butchery behavior at HEB site, with specific interests in the tool use and choice of the species. Understanding how and why *H. erectus* used and preferred certain ESA tool characteristics for butchery purposes is significant in understanding their strategies for mitigating costs of acquiring and processing meat

resources (butchery) (Blumenschine & Pobiner, 2007; Shipman & Walker, 1989). Major evolutionary milestones during the Pleistocene (such as evolution of *H. erectus*' bigger brain) were tied to their ability to obtain high caloric food resources (such as meat) with minimum energetics costs (Bunn, 2006; Isler & Van Schaik, 2014; Pante, 2010; Pante, 2013; Ungar, 2006). The excess caloric return from carnivory provided the energetics budget required to evolve and maintain a bigger brain (Isler & Van Schaik, 2014). Therefore, in order to investigate *H. erectus* tool use and preference during butchery, this study has the following objectives.

1.3 Objectives of the study

The first objective of this study is to apply the discriminant models from Keevil's (2018) experimental study, to the 0.9 Ma cut marked fossil bones from HEB site, Olduvai Gorge, in order to identify stone tool technology (biface or flake) used by *H. erectus* for butchery at that site. This is accomplished by applying Keevil's (2018) quadratic discriminant analyses (QDA) models on the archaeological cut mark data from HEB. Keevil's (2018) QDA classification, uses variations in micromorphological measurements (such as volume, weight, length, width etc.) of the cut marks to discriminate technology of the tools used to create the cut marks. Since HEB is a known Acheulian and *H. erectus* site, results from the study will help us diagnose proportion of usage (from frequencies) between the two prominent Acheulian technologies (flake or biface) at HEB site, around 0.9Ma.

The second objective is to apply the discriminant models from Keevil's (2018) experimental study to the 0.9Ma cut marked fossil bones from HEB site, Olduvai Gorge, in order to identify the raw material types used by *H. erectus* to make stone tools that were used for butchery at that site. Like with the first objective, this is also done by applying Keevil (2018) quadratic discriminant analyses (QDA) models on the archaeological cut mark data from HEB. Capitalizing on the

connection between stone tool properties (raw materials) and resulting cut mark morphology; Keevil's (2018) QDA models use variations in micro-measurements of those cut mark (such as volume of the cut mark, cut mark weight, length, cut mark width etc.) to diagnose raw material types used to create the cut marks.

Butchery studies using contemporary analogies (Jones, 1980; 1981) have demonstrated that technology and raw material properties of stone tools affect their efficiency as animal butchery tools. This efficiency is reflected through the influence of both technology and raw material on the tool's edge durability and sharpness (among others) during a butchery event (Jones, 1981; Key et al. 2020). Therefore, results from this study can illuminate what technology and raw materials were preferred and used by *H. erectus* in making butchery tools at HEB site, and underlying factors for such choices.

1.4 Research Questions

To achieve these objectives, the study seeks to answer the following questions:

First, what ESA technology type (flake or biface) was mostly used by *H. erectus* for butchery at HEB site? Second, what raw material type was mostly used by *H. erectus* for making butchery tools at HEB site? The first two questions can be investigated by looking at the frequencies and proportions of the ESA tools diagnosed from 3D metrological study of the HEB cuts in conjunction with the ESA artifacts found at the site (Leakey & Roe, 1994). This leads to the third question which seeks to determine if the tool frequencies and proportion diagnosed from 3D optical metrology will be reflective of the technology and raw material distribution at HEB site?

1.5 Research Hypothesis

Based on the posed research questions, the study therefore hypothesizes (H_1) that, 3D optical profilometric study of butchery marks at HEB indicate hominin tool use and choice, and that the tool frequencies diagnosed from the 3D optical profilometric study, are reflective of the technology and raw material distribution at HEB site. This means that, in order for this hypothesis (H_1) to be validated, this study has to refute an alternate hypothesis (H_0) that, the 3D optical profilometric study of butchery marks at HEB do not indicate hominin tool use and choice, and that the tool frequencies diagnosed from the 3D optical profilometric study, are not reflective of the technology and raw material distribution at HEB site.

CHAPTER 2 LITERATURE REVIEW

2.0 Theoretical background

This study aims to understand the butchery practices of *Homo erectus* at HEB site by studying the relationship or link between the micromorphology of cut marks found on surfaces of HEB bone assemblage, and ESA tools properties (technology and raw material types). To accomplish this task, the study primarily uses uniformitarianism and middle range theoretical approaches.

One of the necessary assumptions this study makes follows the principle of uniformitarianism proposed by Charles Lyell in 1830s, which states that, the rate of geological change, as well as geologic and natural laws behave and remain constant throughout time and space (Gould, 1965). From this principle, Gould (1965) identifies dual concepts of uniformitarianism, which are; substantive and methodological uniformitarianism. Substantive uniformitarianism is based on the idea that, we can extrapolate present-day observed rates or conditions to past times because they remain constant throughout time. However, recent scientific research has proven that this assumption is no longer valid or true (Cameron, 1993; Gould, 1965). On the other hand, methodological uniformitarianism is based on the idea that the natural and geological laws behave and remain constant throughout time and space – a statement that withstood the test of time and proved to be valid (Cameron, 1993; Gould, 1965).

Therefore, this study employs methodological uniformitarianism which assumes that only the geological and natural laws remain constant through time and space, and therefore allowing natural and observable processes in the present to be considered analogous to similar processes in the past (Cameron, 1993; Gould, 1965). Since this study, uses a model created through actualistic study by

Keevil (2018), it therefore assumes that the processes used to create Keevil's (2018) experimental cutmarks – are similar to processes used by hominins to create cutmarks at HEB site around 0.9 million years ago.

Another theoretical framework employed in this study is the middle-range theory. Middle range theory relies on empirical observations of the processes and principles responsible for the formation of the archaeological record, in order to interpret the past (Binford, 1981; Reitz et al. 1999). Middle range theoretical approach involves the use of empirical and observable analogies in the present to infer dynamic behaviors in the past (Binford, 1981). This can be done through actualistic experimentation aimed at identifying direct cause and effect relationships between a dynamic behavior and the resulting trace. The approach therefore uses, inferences from present day dynamic behaviors, to interpret the static traces recovered from the archaeological record (Binford, 1981; Gifford-Gonzalez, 1991).

Gifford-Gonzalez (1991) developed a nested hierarchical system of relational analogies to link six taphonomic contextual categories together. The system uses empirical and experimentally tested causal relationships, to hierarchically connect a static trace: first to its causal agent, then effector, actor and finally to its broader behavioral and ecological contexts (Gifford-Gonzalez, 1991). As such, both this study, and the Keevil (2018) actualistic research applied in this study; investigates hominin butchery behavior in the archeological record by identifying the causal relationships between cutmark micromorphology (a static trace) and the structural characteristics of stone tools (an effector).

2.1 Bone surface modification (BSM) studies

The core method of this study involves inferring characteristics (technology and raw material types) of ESA tools, from the static cutmark traces left on bone surfaces. The general term, ‘bone surface modification’ (BSM) is used to refer to traces found on bone surfaces, which can either be natural or humanmade. Natural BSMs includes; trampling marks (Courtney et al. 2019; 2020; Fisher, 1995), bioerosion marks (Blumenschine et al. 2007; Dominguez- Rodrigo & Barba, 2006; Prassack & Pante, 2007) and carnivore tooth marks (Blumenschine, 1988; Blumenschine, 1995; Blumenschine et al. 1996; Selvaggio, 1994; Selvaggio & Wilder, 2001). Humanmade BSMs includes; cut marks (Blumenschine, 1995; Blumenschine et al. 1996; Potts & Shipman, 1981) and percussion marks (Blumenschine & Selvaggio, 1988; Blumenschine, 1995; Blumenschine et al. 1996; Capaldo & Blumenschine, 1994).

Taphonomic study of BSMs in zooarchaeology has been evolving in the last four decades. The use of bone surface modifications (BSMs) on fossil assemblages to study and infer early hominin behavior became popular in zooarchaeology during second half of the 20th century (Binford, 1981; Blumenschine & Selvaggio, 1988; Blumenschine et al. 1996; Bunn et al. 1986; Gonzalez, 1991; Fisher, 1995; Potts & Shipman, 1981; Shipman, 1986; Shipman & Rose, 1983). The Majority of these pioneering studies were done at Olduvai Gorge (Bunn et al. 1986; Blumenschine & Selvaggio, 1988; Fisher, 1995; Potts & Shipman, 1981; Shipman & Rose, 1983) partly due to the abundance of well-preserved BSMs on the large fossil assemblages that were being recovered at FLK Zinj site (Bunn et al. 1986). Since then, tremendous improvements have been made in taphonomic studies of bone surface modifications (BSM). These advancements have been growing from simple qualitative diagnosis of actors creating varying traces on fossil bones (such as diagnosing cut marks, tooth marks and other BSMs) (Binford, 1981; Blumenschine, 1995;

Capaldo, 1998; Domínguez-Rodrigo, 1999; Domínguez-Rodrigo and Pickering, 2003; Pante et al., 2012; Selvaggio, 1998; Shipman, 1986) to more quantitative methods (Gumrukcu et al. 2017; Keevil et al. 2018; Maté-González et al. 2015; Muttart et al. 2018; Pante et al. 2017; Yravedra et al. 2017). This study contributes to this body of knowledge by applying quantitative methods developed by Pante et al. (2017) and Keevil's (2018) statistical models for diagnosing ESA technology and raw materials from cut mark traces found on fossil bone assemblages from the HEB site, Olduvai Gorge, Tanzania.

2.2 Cut marks

The primary BSMs investigated in this study are cutmarks. Cut marks on bone surfaces can indicate defleshing, skinning, or disarticulation which implies that cut marks serve as undisputed evidence of carcass access or processing by humans (Blumenschine, 1995; Blumenschine et al. 1996; Fisher, 1995; Potts & Shipman, 1981). What cut marks can tell us about hominins' access or processing of carcasses (hominin butchery behavior) has also been advancing. The early utility of cut marks on interpreting hominin butchery behavior was identification of patterning in the butchering techniques (which is done by analyzing the location and frequency of cut marks on different skeletal parts in conjunction with knowledge of animal anatomy) (Bunn, 1986; Bunn et al. 1986; Bunn & Ezzo, 1993; Marshall, 1986; Shipman & Rose, 1983a; 1983b). These studies are very useful, because location and frequency of cut marks on different skeletal parts can be used to make inferences on hominin timing and access to carcasses (Blumenschine, 1995). This is done by analyzing the overall percentage of cut marks in an assemblage and their positions relative to carnivore tooth marks. Higher cutmark frequency relative to toothmarks on a bone indicates that hominins had first or early access to that carcass followed by carnivores and vice versa. Therefore, cutmark patterning and frequency on fossil bone assemblages can infer different hominin dietary

strategies such as: passive scavenging (late access to carcasses by hominins – mostly exploiting non-meat products like marrow), aggressive scavenging (late access to carcasses by hominins – accessing both meat and marrow) or hunting (hominins have primary access to carcasses, accessing majority of the meat) (Blumenschine, 1995; Blumenschine et al, 2007; Dominguez-Rodrigo & Barba, 2005; Dominguez-Rodrigo & Piquares, 2005; Dominguez-Rodrigo et al, 2010; Dominguez-Rodrigo et al, 2014; Egeland et al, 2004; Pante, 2010; Pante, 2012; Pante et al, 2012; Pickering & Dominguez-Rodrigo, 2006; Pobiner, 2007).

2.3 Different methods of modelling mark morphology

Correct diagnosis of BSM is very crucial considering the implications attached. Previously, equipment like handheld lenses, or low power optical stereomicroscope (Blumenschine et al. 1996; Bunn, 1981) with natural light were used to identify different BSMs (Blumenschine, 1995; Blumenschine et al. 1996; Fisher, 1995; Potts & Shipman, 1981; Selvaggio, 1994; Shipman, 1986; Shipman & Rose, 1983). This method involved looking for qualitative traits (For example, the cross section of a carnivore tooth mark under a microscope appeared to be ‘U-shaped’ while that of a cut mark was considered more ‘V-shaped’) that could broadly discriminate different agencies/actors (carnivores for tooth marks and hominins for cut marks) (Fisher, 1995). Recent diagnoses of BSMs have progressed towards classifications made from multiple qualitative and quantitative micromorphological and morphometric traits of the BSMs. The micromorphological data is obtained using high-resolution modelling techniques such as scanning electron microscope (SEM), micro-photogrammetry, and 3D optical profilometry/metrology (Fisher, 1995; Pante et al. 2017).

2.3.1 Scanning electron microscope (SEM)

Pioneering use of scanning electron microscope (SEM) in archaeology started in 1980's, with observation of surface topography of archaeological materials (such as metals, glass, faience, pottery, stone, soil particles, pigments, bone, teeth, fingernails, skin, hair, eggshell, mollusks, insects and parasites, plant remains, wood, pollen, fibers etc.) being the primary objective (Fisher, 1995; Freestone & Middleton, 1987; Olson, 1988; Potts & Shipman, 1981). In terms of studying cut mark traces and other bone surface modifications, Fisher (1995) identified various strengths of SEM such as; continuous magnification over a much greater range, high resolution, increased depth of field, and the capability to make high quality microphotographs. These descriptions were based on comparisons with other microscopes at that time and may no longer be viable or sound if weighed against modern microscopy technologies. However, SEM remains the earliest method for producing high quality images of surface topography and was superior to the hand lens or other optical magnifying instruments (such as low power optical stereomicroscopes) when it came to producing models of cut mark micromorphology (Fisher, 1995). SEM has some disadvantages, including; high operating costs (expensive to buy the instruments), time-consuming, and challenges related to preparation and examination of specimens (Fisher, 1995; Fram, 2014).

2.3.2 Micro-photogrammetry

Micro-photogrammetry showed promise as a slightly cost-accessible, and analytically less expensive alternative to SEM (Maté-González et al. 2015). The technique incorporates treatment of high-resolution images with macro-photogrammetry and computer visualization for tri-dimensional reconstruction of cut marks on bones. These micromorphological data are later analyzed (classified) quantitatively using statistical methods (Maté-González et al. 2015). The method was developed using experimental datasets, where variations in microscopic

geomorphometric measurements of cut marks modeled with macro-photogrammetry (such as width along the cut mark, opening angle, and cut mark depth) were used to discriminate cut marks from other types of trace marks (BSMs) using statistical models (Maté-González et al. 2015). Yravedra et al (2017) applied this method on archaeological data sets from BK (Bell's Korongo) site, Olduvai Gorge, and went further by demonstrating that the method could be used to diagnose different stone tool raw material types from the cut marks.

However, this method faces multiple replicability, inter-observer objectivity, and testability challenges (Keevil, 2018). For example, measurements of the deepest part of the profile can significantly vary from measurements of the central profiles of the same mark. This shows that multiple cross-sections of a single mark, can vary in profile measurements, depending on the position in the mark where that profile was taken from (Keevil et al. 2018; Maté-González et al. 2015; Pante et al. 2017). Furthermore, the average time used to analyze one cut mark is considered too long (50 minutes) compared to other modern alternatives.

2.3.3 3-D optical profilometry/metrology

Advent of high-resolution 3D scanning methods in BSM studies steered scientists to develop discipline-wide, objective and replicable protocols for diagnosing effector (tools) from cut mark micromorphology (trace). Among such efforts, were Bello & Soligo (2008) who presented a scanning method that allowed 3D reconstruction of cut mark micromorphology and quantification of profile parameters. Their technique used quantitative measurements of cut mark cross-sectional shape, shoulder heights, sharpness as well as inclination and depth of a cut; to characterize cut marks based on tool effectors (Bello & Soligo, 2008). When developed the method was used to discriminate between experimentally created cut marks made by metal knife from unretouched flints (Bello & Soligo, 2008). The method was then expanded and applied to archaeological

butchery marks made by handaxes (Bello et al. 2009), and to slicing marks found on human teeth (Bello, 2011). Boschini & Crezzini (2012) also conducted a 3D microscopic analyses of bone surfaces in order to identify origin of different kinds of marks on bones. They used a HIROX Digital Microscope KH-7700 to obtain morphometric measurements of cut marks (such as depth, breadth, angles etc.), which were then used as objective criteria for identifying origin of cut marks (effector tools) through statistical analyses. However, one of the greatest critiques for these pioneering 3D microscopic methods of studying BSMs, is lack of inter- analysts' reproducibility (Keevil, 2018; Pante et al. 2017). This limits the methods' ability to identify meaningful or informative trends in the micromorphological characteristics of cut marks (Keevil, 2018, p.22)

Recently, Pante et al. (2017) overcame the problems of replicability and testability in 3-D scanning methodologies, by creating a standardized and quantitative protocol for diagnosing cut marks, using 3D reconstruction and measurement of the micromorphological features (such as surface area, volume, depth, length etc.) of the cut mark. The replicability of this methodology has been tested using an inter-observer approach with promising results, which showed that this methodology is both replicable and accurate (Keevil et al. 2018; Pante et al. 2017). This protocol has been expanded and developed over the years to include models that distinguish cut marks from tooth marks with 97.5% accuracy (Pante et al. 2017), classification of different tooth marks based by actors or carnivore taxa (Muttart et al. 2017), assessing effects of fluvial action on cut mark micromorphology (Gumrukcu et al. 2018; Gumrukcu & Pante, 2018), and classifying cut marks made by specific raw material and technology types (Keevil, 2018; Keevil et al. 2018). Many of these studies were applied to archaeological samples with promising results. This study uses the same protocol in trying to predict raw material and technology type from HEB cut mark micromorphology.

2.4 Early Stone Age (ESA) Technology

The Early Stone Age marks a very crucial time in human history, as hominins, through tool making and use, were able to expand their niche for efficient access to animal carcass products. The ESA (Early Stone Age) is dominated by two well-known stone tool industries. The Oldest – Oldowan industry (from 2.8 to 1.6 million years ago), was as the name suggests, first discovered at Olduvai Gorge by Louis Leakey in 1930's (Leakey, 1936). The term “Oldowan” was first used by Louis Leakey in 1936 to describe materials at Olduvai Gorge predating Acheulian handaxes and cleaver industries, which at that time were already known to archaeologists (Leakey, 1936; Schick & Toth, 2006). Technology of the Oldowan industry is relatively simple and involves flexible breakage of cobbles in order to obtain sharp edges. The Oldowan toolkit is made up of several tool types such as flakes, choppers, hammer stones, scrappers, anvils, polyhedrons, discoids, occasional subspheroids and burins (Leakey, 1971; Schick & Toth, 2006).

Around 1.7Ma, the Oldowan industry was replaced by the Acheulian industry or techno-complex (de la Torre, 2016). The Acheulian industry is the second and the longest lasting in prehistory, lasting from 1.7 Ma to 0.1 Ma (de la Torre, 2016). Technology of the Acheulian industry is made up of: biface handaxes (usually ranging between 13 and 25 cm in length and shaping covers less than 50% of the surface), cutting tools (LCTs), cleavers, flakes, picks, and bifaces made on flakes and cobbles (de la Torre, 2016).

Research on emergence of the Acheulian technology or transition from Oldowan to Acheulian technology is still ongoing (Arroyo & de la Torre, 2018; Bibi et al. 2018; de la Torre et al. 2012; de la Torre & Mora, 2014; de la Torre, 2016; de la Torre et al. 2018; McHenry & Stanistreet, 2018; McHenry & de la Torre, 2018; Prassack et al. 2018; Uno et al. 2018). However, one of the central questions is whether these emerging bifacial tools (in the Acheulian industry)

were used for the same butchery purposes as the Oldowan flake tools or served a different function, for example sexual selection (because of aesthetic properties presumed to be in the tear-dropped shaped of the Acheulian tools) (Kohn & Mithen, 1999; Mithen, 2003).

This study, and other research (Keevil, 2018; Maté-González et al. 2018; Yravedra et al. 2017) on cutmark micro-morphology can inform us on how different tool types (Oldowan flakes vs Acheulian bifaces) were used in an archaeological butchery event. Taphonomic studies on cut mark micro-morphometrics can identify specific ESA tool types used by hominins during butchery, and thus provide better understanding on butchery functions of different stone tool technologies of the ESA industries (Keevil, 2018; Maté-González et al. 2018; Yravedra et al. 2017).

2.4.1 ESAs technology at HEB site, Olduvai Gorge

Even with improved methods for studying cut mark micromorphology, there aren't many ESA sites that can offer well preserved cut marks that are in association with ESA artifacts (Bunn et al. 1986). Olduvai gorge is suitable for BSM studies, because it contains sites like HEB, that have well dated artifacts that are in association with cut marked fossils bones (Bunn, 1986; Bunn et al. 1986; Leakey & Roe, 1995). The HEB site is 0.9 million years old, and stratigraphically located in Lower Bed IV (geological beds at olduvai, identified by their sedimentological composition, color, and sometimes artifact composition). Based on artifacts assemblages (more than 40% handaxes) and temporal contexts, the HEB site is considered to be an Acheulian site, and is associated with the species *Homo erectus* (Leakey & Roe, 1994; Njau et al. 2020).

In terms of raw material distribution at the site, HEB site is dominated by quartzite and lava. Earliest well detailed accounts of raw materials found at the HEB site came from M.D Leakey's excavations during 1960's (Leakey & Roe, 1994) where she documented the raw material

composition at HEB to be primarily quartzite (63.5%) and lava (a composite name used in this study to include phonolite, basalt and/or any volcanic rock) which made up 31.9%. In level 4, Leakey & Roe (1994), found that quartzite made up 81.4% of the total assemblage (n=1110), followed by basalt (lava), which made up 14.2% of the assemblage (see table 2.1).

Table 2. 1: Re-make of a table from Leakey & Roe (1994), showing ESA raw material distribution at HEB site (level 3 & 4).

Stratigraphic Level	Quartzite*	Lava (Phonolite & Basalt) *	Chert
Level 3	588	315	0
Level 4	903	203	0

**Quartzite (includes fine-grained quartzite), Lava (includes phonolite, basalt, trachyte, and other volcanic rocks). Unlike in Leakey & Roe (1995), this re-make of raw material distribution table should be interpreted independent of stone tool technology.*

Technology-wise, HEB has an abundance of flake tools and bifaces. Mary Leakey reported that out of 303 lithic materials recovered from HEB site (level 3), a significantly large portion (n=201) of the assemblage was made up of flakes (66.3%), while bifaces made up about 33% of the assemblage (n=100), and cores made up about 0.6% (n=2) of the assemblage. In level 4, she found that flakes made up about 72.5 % (eq. 158 specimens) of the total assemblage (n=218), followed by bifaces – which made up about 27.5% (60 specimens) of the assemblage. At level 4, Mary Leakey did not record any core tools (see Table 2.2).

Table 2. 2: Produced from table from Leakey & Roe (1994), showing ESA technology distribution at HEB site (level 3 & 4).

Stratigraphic Level	Flake*	Biface	Cores
Level 3	201	100	2
Level 4	158	60	0

Recently the HEB site was re-excavated by OGCP (Olduvai Gorge Coring Project) where they recovered several thousand ESA tools and fossil bones from multiple levels of their two trenches (T4 & T5) (Njau et al. 2020). While studies on the ESA artifacts ($n = 3500$) recovered by OGCP has not yet been published, preliminary findings indicating abundance of ESA artifacts associated with cut marked fossil fauna has been reported in Njau et al (2020). This study will be applying Keevil (2018) classification models on some of the cut marks found on these fossil bones recovered by OGCP at HEB T4 & T5.

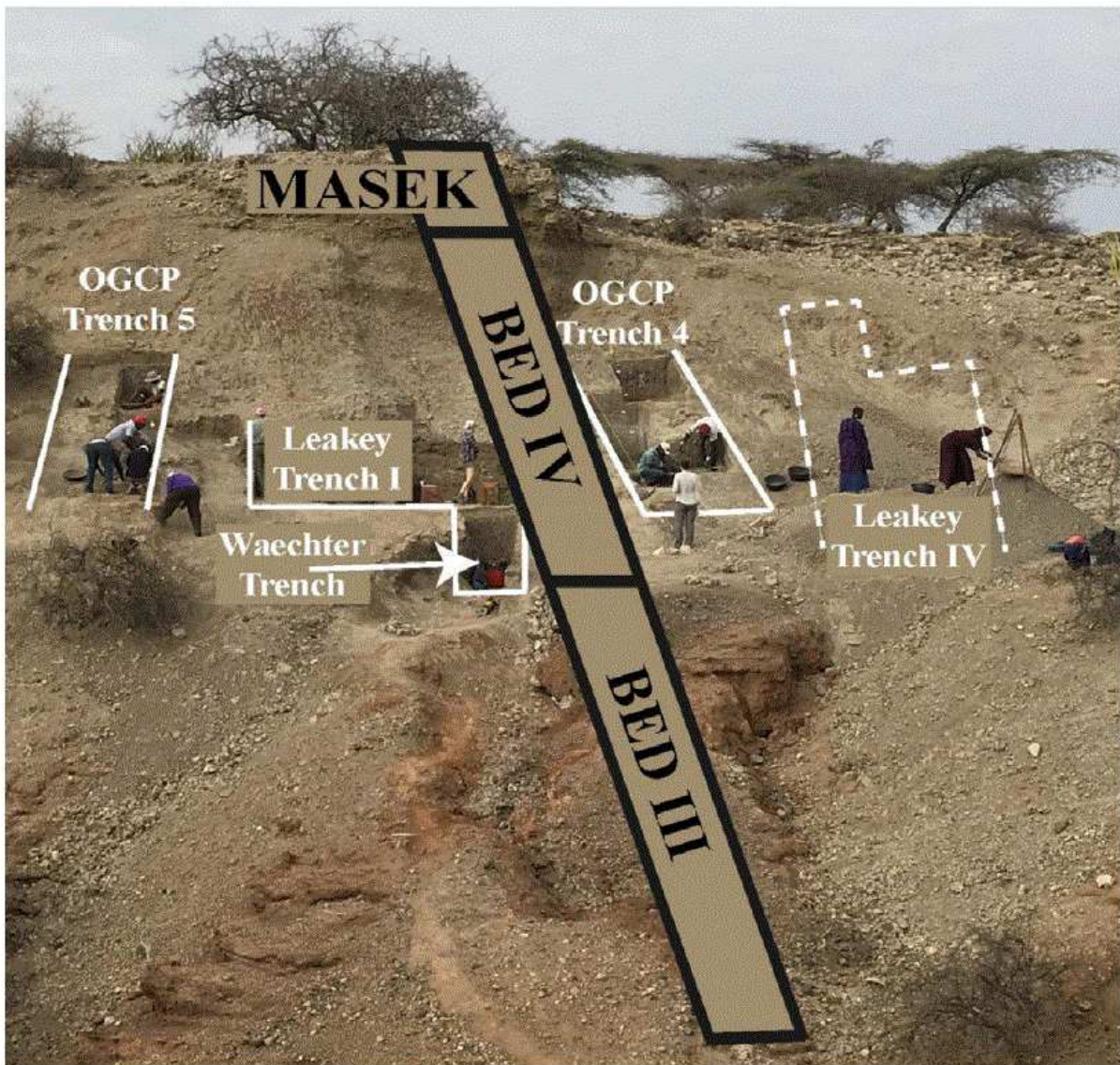


Figure 2. 1: Image showing the ongoing OGCP excavations at HEB site (OGCP Trench 4 & 5) and adjacent trenches that were excavated by Mary Leakey in 1960's. (source: Njau et al. 2020).

2.5 Cut mark utility on interpreting *Homo erectus* butchery behavior

Generally, the recovered cut mark traces from HEB site, offer significant taphonomic insights into how the assemblage was formed, and ecological behaviors of the actors (*H. erectus*). Presence of cut marks from butchery practices (defleshing, cutting, scraping and disarticulation of animal carcasses), are undisputed evidence for meat access by hominins. Higher frequency of cutmarks on a carcass, has been used infer early (first) access to those carcasses by hominins or access to significant quantities of meat resources by hominins, which implies hunting or aggressive scavenging mode of subsistence (Blumenschine, 1995; Blumenschine et al, 2007; Dominguez-Rodrigo & Barba, 2005; Dominguez-Rodrigo & Piquares, 2005; Dominguez-Rodrigo et al, 2010; Dominguez-Rodrigo et al, 2014; Egeland et al, 2004; Pante, 2010; Pante, 2012; Pante et al, 2012; Pickering & Dominguez-Rodrigo, 2006; Pobiner, 2007). Recent methods (Keevil, 2018; and this study) allows identification of the technology and raw material types that were used to create such cut mark traces – offering more insights into high order inferences of hominin behavioral ecology attributes such as: land use patterns (from relations such as original raw material sources and tool frequencies at a site), tool manufacture, tool use (such as differences in utility between tool made by different technologies – flakes and handaxes or between tools made of different raw materials, budgeting and resource allocation behaviors of hominins and many more.

CHAPTER 3 MATERIALS AND METHODOLOGY

This study uses the 3D optical metrology protocols designed by Pante et al (2017) for collection and processing of cut mark micro-morphometrical data, and applies them to compare an actualistic database of cut mark measurements created by Keevil (2018) to interpret cut marks found on fossils in the HEB assemblage.

3.1 Experimental Sample

This study uses Keevil's (2018) experimental data to train, the multivariate Quadratic discriminant analysis models that use variations in cut mark micromorphology to diagnose (classify) specific raw materials and technology types (flakes and bifaces). The Keevil (2018) experimental data came from bones that were collected with an emphasis on keeping bone surface and materials as consistent as possible (Keevil, 2018). Keevil (2018) bone collection involved sectioned bovid femur and tibia midshafts that were obtained from Beaver's Market, a local butcher in Fort Collins, Colorado (Keevil, 2018). Those bones were sectioned transversely across the bone shaft using a mechanized bone saw. Then Keevil (2018) only used hind limb long bone midshafts in his study, in order to keep cortical bone density consistent throughout all cutting trials - allowing for better cut mark comparability and experimental control (p. 26).

All bones analyzed in Keevil (2018), were from size four bovid (in this case a cow), which includes all animals that weigh between 750 and 2000 pounds (based on animal size class definitions established by Bunn (1982) (Keevil, 2018). Keevil, then removed any remaining flesh from the surface of each bone using plastic knives and wooden skewers as to not alter the bone surface, leaving only the periosteum intact and preventing unintentional bone surface markings.

All bone surfaces were thoroughly inspected before proceeding with the study to identify pre-experimental bone surface marks. The location of these marks was noted to ensure that any pre-study bone surface modifications were not confused with experimentally created cut marks. The Keevil (2018), randomly assigned tibia and femur bones to each tool class during the cutting trial portion (Table 3.1). A total of 256 cut marks were made in this experiment and will be used in this study as the training dataset.

Table 3. 1: Number and type of hind limb bones used in Keevil (2018) for each cut mark group.

Cut mark group	ID	Bone	Cut mark group	ID	Bone
Quartzite Biface	1	Tibia	Chert Biface	1	Tibia
	2	Femur		2	Tibia
	3	Tibia		3	Tibia
Quartzite Flake	1	Tibia	Chert Flake	1	Tibia
	2	Tibia		2	Tibia
	3	Femur		3	Femur
	4	Femur			
Basalt Biface	1	Femur	Phonolite Biface	1	Tibia
	2	Tibia		2	Tibia
	3	Tibia			
Basalt Flake	1	Tibia	Phonolite Flake	1	Tibia
	2	Femur		2	Femur
	3	Femur		3	Tibia

3.2 Archaeological Sample

The archaeological sample of fossil trace marks used in the study were collected from fossils recovered from the HEB site, by the OGCP (Olduvai Gorge Coring Project) research team. This site is dated to about 0.9 million years ago. This particular period is preferable for this study because it is contemporaneous with *Homo erectus* and Acheulian techno complex (Njau et al. 2020). Mary Leakey's excavation and analyses information regarding raw material and technological distribution for HEB site (Leakey & Roe, 1994), is also used here to inform interpretations in this study.

3.3 Diagnosing Cut Marks using 3D optical metrology

Cut marks traces on the fossilized bone surfaces were initially qualitatively identified by Dr. Michael Pante using natural light and a hand lens – in accordance to standard protocols described by Blumenschine et al (1996). Then a total of 110 cut marks from 66 fossil bones were scanned following Pante et al's (2017) protocol for BSM diagnosis. The scanning process was done on site, in one of OGCP's field laboratories at Olduvai Gorge – using SENSOFAR® S Neox non-contact 3D optical profilometer; which generated 3-dimensional models of cut mark micromorphology that were viewed using Sensoview® software.

3.4 Processing 3D data using SensoMap Standard Version 7.4

All measurements and analysis of the 3D cut mark models were done in the 3-D imaging and analysis laboratory at Colorado State University (CSU), Fort Collins, Colorado. The 3D cut mark models were exported from the Sensoview® software to another software called SensoMap® (standard version 7.4) for metrological measurements. Out of the scanned 66 3D cutmarks, a sample of ($n= 20$) was non-randomly selected for measurements (Table 3.2), based on analytical

criteria – mainly related to quality of the scan (3D model). Furthermore, cut marks that crossed on top of each other and cut marks that were superimposed on other types of marks (such as trampling, weathering etc.) were not selected for measurement.

Table 3. 2: Fossilized trace marks from HEB analyzed in this study.

ID	Skeletal Element	Body Size	Number of Marks
HEBT4_L7_195-1	Rib	Shaft	1
HEBT4_L7_232-1	Tibia	Epiphysis	1
HEBT4_L8_147-1	Lumbar	Spine	1
HEBT4_L8_188-1	Femur	Midshaft	1
HEBT4_L8_223-1	Femur	Midshaft	1
HEBT4_L8_232-1	Femur	Midshaft	1
HEBT4_L8_294-2	Radius/Ulna	Epiphysis	1
HEBT4_L8_351-1	Long bone	Midshaft	2
HEBT4_L8_359-1a	Tibia	Near Epiphysis	2
HEBT4_L8_372-1	Radius	Midshaft	5
HEBT4_L8_359-2	Tibia	Near Epiphysis	2
HEBT4_L8_373-2	Radius	Midshaft	1
HEBT4_L8_391-1	Long bone	Midshaft	1
HEBT4_L8_468-2	Tibia	Midshaft	1

Using the SensoMap® software, the 3D cut mark models were processed, starting with an ‘operators’ studiable called “Extract layers” found in the software. This strips away visualization noise on the model to create a “topographic layer” as shown in the figures below.

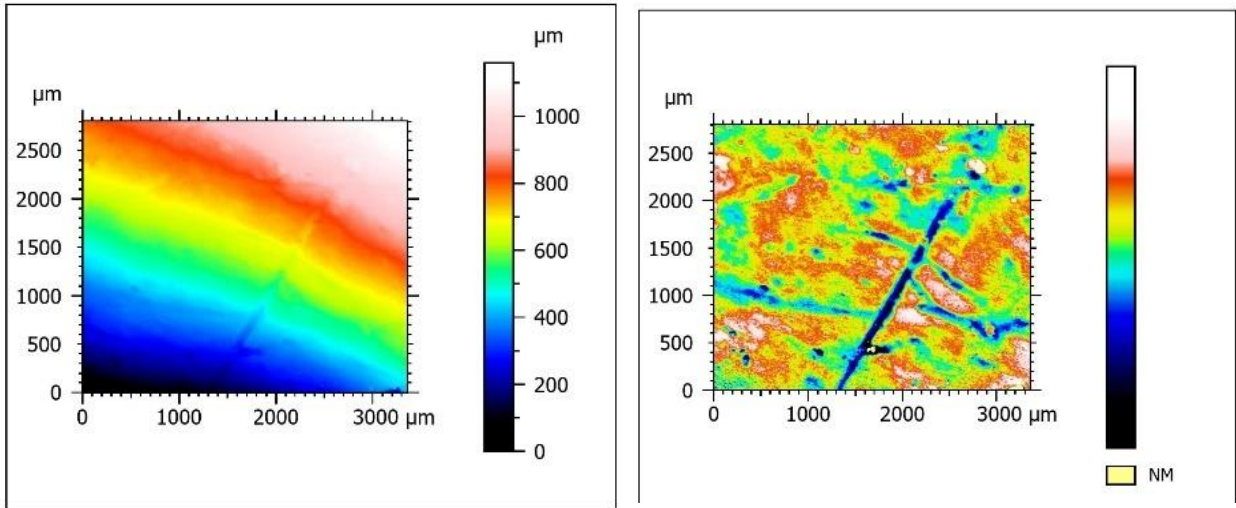


Figure 3. 1: Left image shows the original 3D cut mark model after importing it from Senso view®. Right image shows the same 3D model after removing the “3D layer” (also called Topographic layer). Color scales (on far right of both images) indicate depth, from (white = shallow) to Black = deep)

For marks that are slanted (this depends on how the bone or mark was positioned relative to the optical pen or objective during the scanning processes), it is good practice to rotate them into a straight vertical line and Pante et al (2017) has demonstrated that slanted marks can reduce accuracy of other measurements on the marks (measurements that require tracing of the mark to assign points).

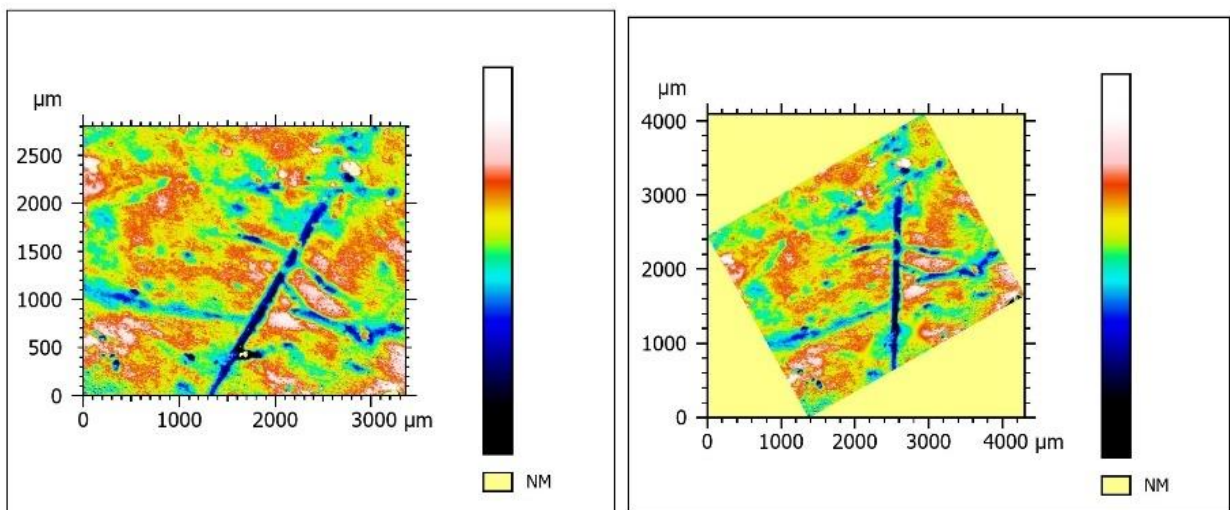


Figure 3. 2: left image shows a side-ways slanted 3D model of the mark. Right image shows the same 3D model after being rotated towards left one time – to make it vertically straight.

Then, an ‘operator’ studiable named “fill in NM” (fill in missing/non-measured points) was applied to the 3D models. This algorithm fills any missing points that were not captured during the scanning process. Then, influence of the shape of the bone on the actual shape of the cut marks was removed by the software’s algorithm, through an ‘operator’ studiable named “remove form” set at a polynomial degree of 2. Then, after applying the operator studiabilities - “threshold” (that defines extent of the mark’s profile) and “fill in NM” (for the second time); the area of the mark (by closely tracing the cut mark on the 3D model) was extracted using an operator studiable named “extract area”.

3.5 Measurements of 3D cut mark models

Similar to processing the 3D cut mark models above, the measurement process followed Pante et al (2017) protocol. Initial measurements included Maximum length (μm) and width measurements (μm), which were recorded using the “distance” tool provided by the SensoMap Standard Version 7.4® software. Length was taken as the maximum distance from one end of a cut mark to the other and could be measured in multiple increments if the cut mark was not straight. Width was recorded perpendicular to this length measurement and was taken along the widest part of the entire cut mark. Then, volume (μm^3), surface area (μm^2), maximum depth (3-D) (μm), and mean depth (μm) measurements were recorded using the “volume of a hole” function provided by the software.

During volume of a hole measurements, the software allows users to manually outline the boundary of a mark using a series of interconnected points and records the measurements from within this defined area (Figure 3.5 below). This tool uses a least squares plane parameter to create a covering overtop of the cut mark, which represents an estimation of the pre-cut mark bone surface

and allows 3-dimensional volume measurements to be recorded from within this enclosure (Pante et al. 2017).

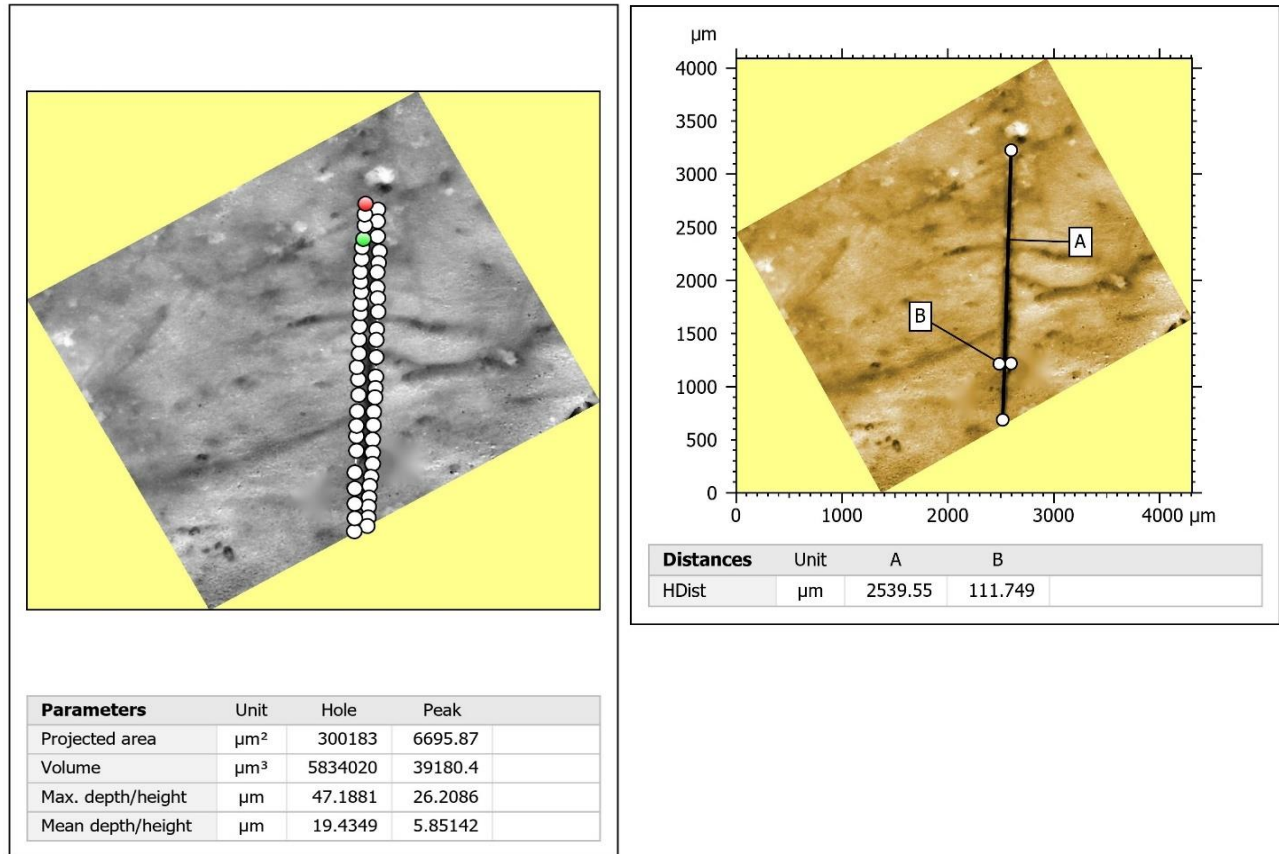


Figure 3. 3: volume of a hole measurement from a 3D model of the mark (left). This studiabile yields multiple cut mark measurements such as surface area, volume, maximum and minimum depths or heights. Right image shows distance measurements of the mark (Length \times Width) from a 3D model of the cut mark

3.6 Measurements of cut mark profiles

A profile was then extracted from the 3D cut mark model (through the lowest point in the mark). Following Pante et al (2017) protocol, variables measured from the extracted profile include depth, area, width, roughness (Ra), opening angle and floor radius. The “area of a hole” function was used to measure depth and area of mark profiles. The “under the waterline” option was used because it most accurately identified the edge of marks. The function works by filling in the mark

to the lower of the two edges, effectively eliminating mark shoulders from influencing depth and area measurements. The use of the “under the waterline” option is important to enhance comparisons between cut marks on modern and fossilized bones where shoulders can be lost due to exfoliation or abrasion (Pante et al. 2017, p. 5).

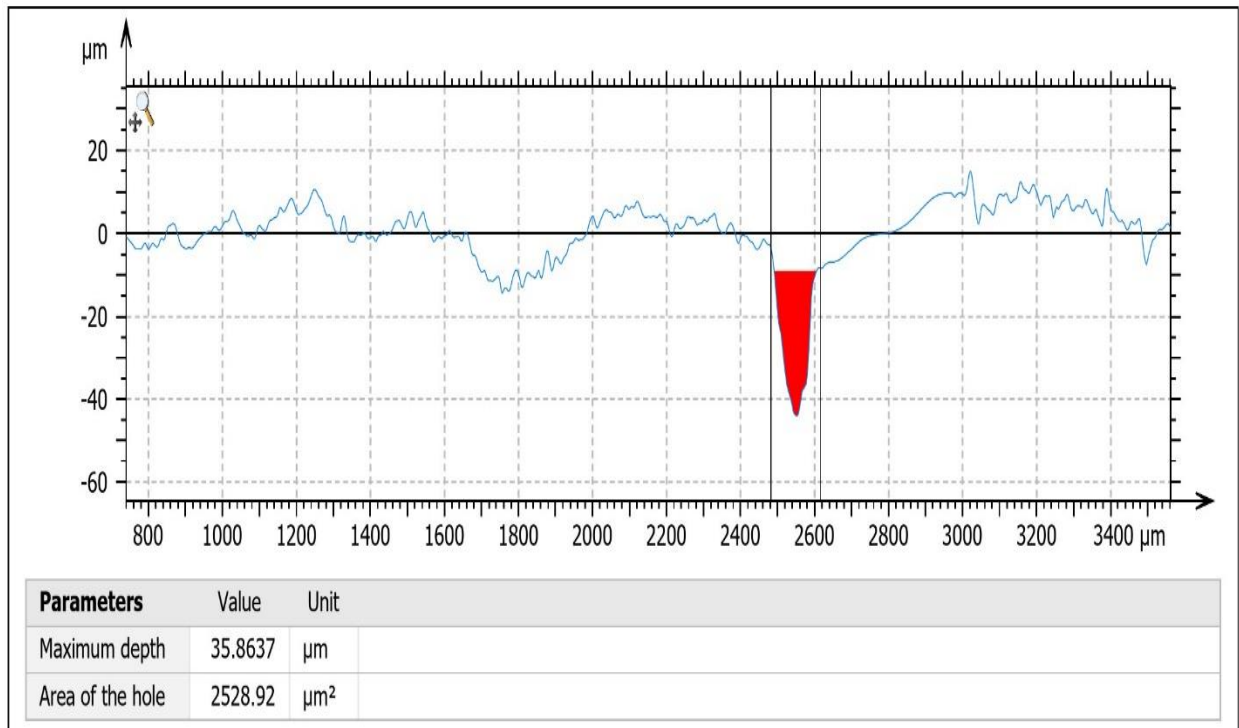


Figure 3. 4: image (above) showing profile measurements for area of a hole (under the waterline)

The maximum width, roughness, angle and floor radius measurements are based on the portion of each profile that reflects the actual mark. The x-coordinates for both edges of the mark were taken from the “area of a hole” studiable and the portion of the profile in between these coordinates was isolated using the “extract area” function. The length of the new profile was recorded as the maximum width of the mark. Roughness (Ra) was measured from the modified profile using the “parameters table” function of the program and is defined as the arithmetic mean deviation from the roughness profile, which is the mean line recorded in the evaluation length.

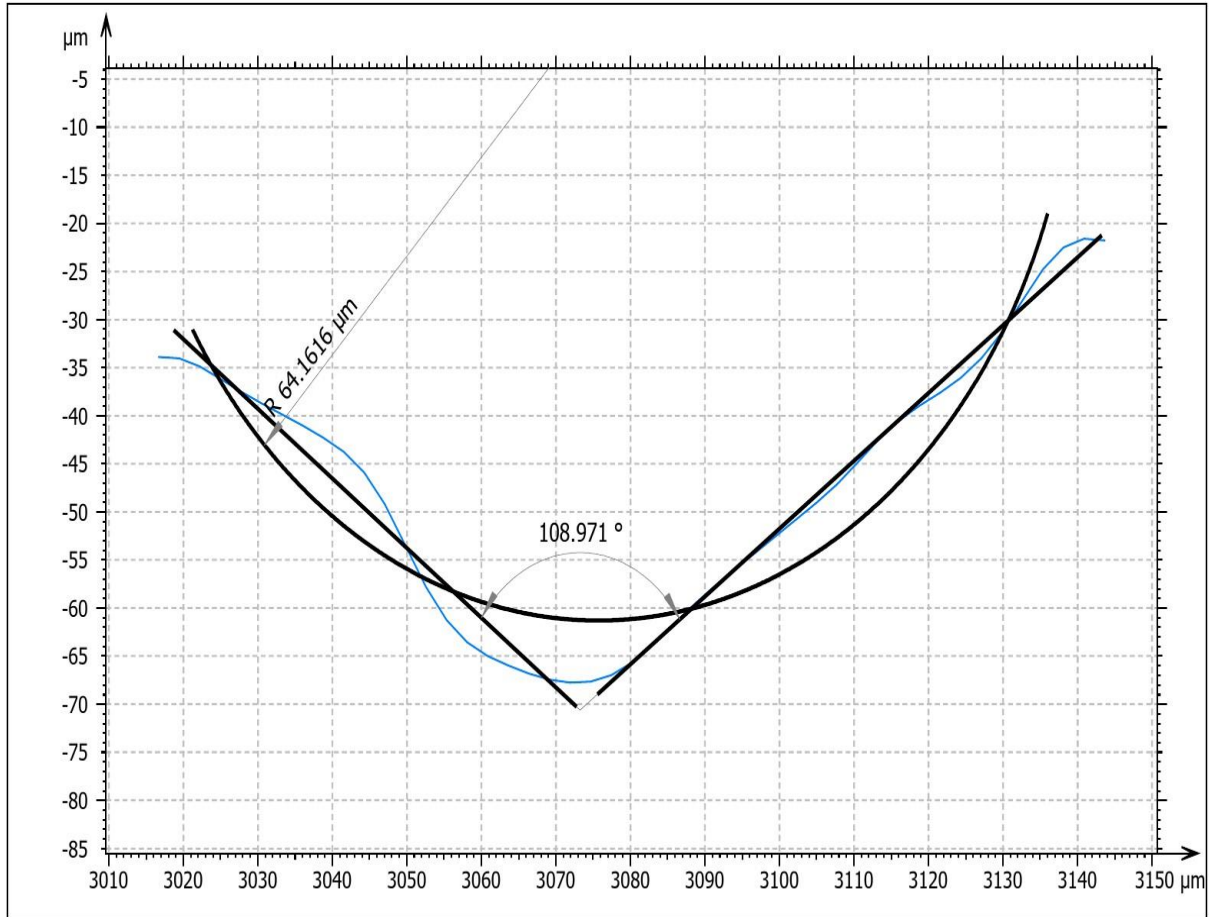


Figure 3. 5: image (above) showing cut marks profile measurements of the opening angle and floor radius

The “contour analysis” function was used to find the opening angle and floor radius of each mark (Figure 3.7). Opening angle was measured by first drawing two segments and then calculating the angle between them. One segment was drawn from the first measured point to the deepest point and another from the deepest point to the last measured point. The segments represent a best fit for all of the points between the two that are selected. The floor radius was found by drawing an arc between the first and last point of the profile. The arc represents a best fit for all of the points in the profile (Pante et al. 2017, p. 5)

3.7 Statistical analysis

Statistical analyses were performed using Microsoft Excel, PAST-Paleontological Statistics Software Package 4.03 and JMP® Pro 15.0.0 (SAS Institute Inc, 2019). Since the goal is to use Keevil (2018) experimental data and statistical model, this study followed all of Keevil's analytical procedures so as not to affect replicability of results.

3.7.1 *Data exploration*

Following Keevil et al (2018), cut mark data used in the analysis was grouped into eight categories based on the technological form and raw material of the tool that created each mark. Then, Shapiro-Wilks tests were used to identify whether each recorded measurement was normally distributed for all cut mark groups. These tests were conducted using the statistical PAST 4.03 software, and following Keevil (2018), measurements indicating the presence of at least one non-normally distributed group were corrected using Box-Cox transformations. Optimal lambda values (Table 4.1) for the Box-Cox transformations were calculated using the PAST software as well.

The final multivariate data exploration analysis done was predictor screening analysis, which examined contributions or influence of individual cut mark measurement to the models. In a much simpler version, the predictor Screening test on JMP software was useful in showing which cut mark measurements are more influenced by technological variations and less influenced by raw material variations, versus those that are more influenced by raw materials and less influenced by technological variations. This information is useful, even for future research in deciding best measurements (variables) to use as predictors for raw materials and or technology.

3.7.2 Multivariate analysis: Quadratic discriminant analysis (QDA)

Quadratic discriminant analyses (QDA), as a standard approach to supervised classification problems where within-group covariance matrices are not assumed equal - was used for this study. This was preferred because Keevil (2018) had already identified the lack of homogenous variance-covariance matrices across groups from the Box's M tests he had conducted in R (Keevil, 2018).

Quadratic discriminant analysis, models the likelihood of each class as a Gaussian or normal distribution, then uses the posterior distributions to estimate the class for a given test point (Srivastava et al. 2007). The Gaussian parameters for each class can be estimated from training points using maximum likelihood (ML) estimation. This Gaussian model assumption is best suited when there isn't much information to characterize a class. For example, if there are too few training samples to infer much about the class distributions (Srivastava et al. 2007). The QDA analyses done in this study, were performed using the "QDA" function found under the multivariate analysis in JMP® Pro 15.0.0.

A total of seven (7) quadratic discriminant models (QDA) were created using JMP® Pro 15.0.0. Three 'raw material' models, three (3) 'technology' models (using 3D measurements only, using profile measurements only, and using both 3D and Profile measurements) and finally, a comprehensive QDA model predicting both raw material and technology at once using all the 12 variables.

Before running the raw material model, a 'shrink covariances' option was checked (this was only done for the raw material model). This JMP algorithm shrinks off the diagonal elements of covariances to improve stability and hence reduce variance of prediction. In all QDA models, a 90% (training): 10% (testing) split of the dataset was set on JMP for cross validation of the model's accuracy.

CHAPTER 4 RESULTS

4.1 Data exploration results

4.1.1 *Normalization: Box-Cox transformations*

Shapiro-Wilk tests for normality that was conducted individually on all measurements for each cut mark group (Appendix A and B), indicated a non-normal distribution for multiple cut mark groups. Therefore, a Box-Cox transformation was applied individually to all twelve variables (measurements) used in the study for both the experimental dataset (from Keevil, 2018) and the archaeological sample. Like Keevil (2018), the lambda values used in the transformation (Table 3.3) were automatically generated by the Paleontological Statistics Software (PAST).

Table 4. 1: Optimal lambda values applied for each Box-Cox measurement transformation.

Categories	Measurement (Variable)	Optimal Lambda values
3D Measurements	Surface Area (SA)	-0.103619
	Volume (VOL)	-0.131457
	Maximum Depth (MD)	-0.596197
	Mean Depth (MEAN)	-0.2694409
	Maximum Length (ML)	-0.210894
	Maximum Width (MW)	-0.43252
Profile Measurements	Maximum Depth (MDP)	-0.406873
	Area (A)	-0.212219
	Width (W)	-0.180908
	Roughness (RA)	-0.102344
	Angle (ANG)	2.18259
	Radius (RAD)	-0.194121

4.1.2 *Univariate detection for outliers*

The univariate distribution of the dataset analyzed in JMP made sure that categorical columns were coded correctly (checking for data recording errors, typos, or difference in coding after combining archaeological and experimental datasets), as well as checking for univariate outliers

for individual measurements groups (Figure 4.1). Comprehensive results (distribution, quantile and summary statistics) of the univariate distributions for each measurement, are attached at the end of this study (Appendix B), and they depict box plot distribution of each measurement (row) as well as outliers found on those measurements.

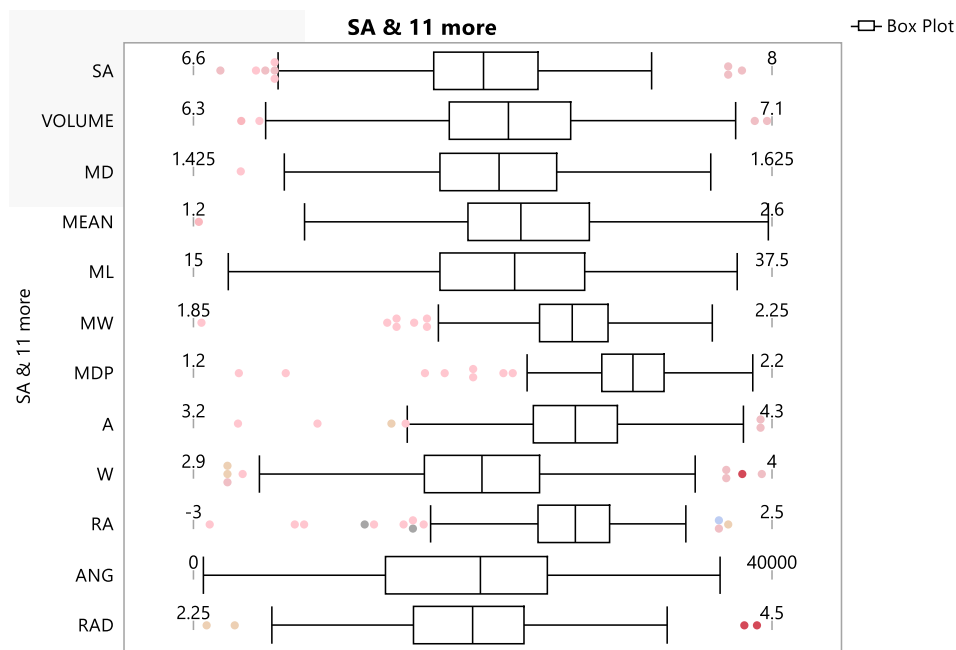














Figure 4. 1: Univariate Box Plot distribution showing rows that have outliers for each of the 12 numeric variables (columns) in the combined dataset/table (experimental + archaeological tables)

4.1.2 *Predictor Screening analyses*













The final multivariate data exploration analyses examined contributions or influence of individual cut mark measurement to the models. In a much simpler version, the predictor Screening test on JMP software was useful in showing which cut mark measurements are more influenced by technological variations and less influenced by raw material variations, versus those that are more influenced by raw materials and less influenced by technological variations. This information is useful, even for future research in deciding best measurements (variables) to use as predictors for raw materials and or technology.

Table 4. 2: Experimental dataset- Predictor Screening for “TECHNOLOGY” Model

Predictor	Contribution	Portion	Rank
SA	6.1751	0.0816 	5
VOLUME	6.6891	0.0884 	4
MD	2.7311	0.0361 	12
MEAN	4.5520	0.0602 	8
ML	10.9488	0.1447 	2
MW	15.2384	0.2014 	1
MDP	3.2044	0.0424 	10
A	7.8706	0.1040 	3
W	5.9571	0.0787 	6
RA	2.8818	0.0381 	11
ANG	4.3934	0.0581 	9
RAD	5.0213	0.0664 	7

***Top 3 best contributors (in green) and top 3 least contributors (in red)*

Table 4. 3: Experimental dataset – Predictor Screening for “RAW MATERIAL” Model

Predictor	Contribution	Portion	Rank
SA	4.6540	0.0615 	6
VOLUME	10.3851	0.1372 	2
MD	7.6646	0.1012 	4
MEAN	15.3330	0.2025 	1
ML	4.4398	0.0586 	7
MW	4.2835	0.0566 	9
MDP	6.2085	0.0820 	5
A	7.7643	0.1026 	3
W	4.2417	0.0560 	10
RA	4.0581	0.0536 	11
ANG	4.2886	0.0566 	8
RAD	2.3829	0.0315 	12

***Top 3 best contributors (in green) and top 3 least contributors (in red)*

4.2 Multivariate analyses results: Quadratic discriminant analyses (QDA)

A total of seven (7) quadratic discriminant models (QDA) were created using JMP® Pro 15.0.0. Three ‘raw material’ models, three (3) ‘technology’ models (using 3D measurements only, using profile measurements only, and using both 3D and Profile measurements) and finally, a comprehensive QDA model predicting both raw material and technology at once using all the 12 variables. Only results for the three models (Raw material only, technology only, and ALL) will be shown in this chapter, along with the 20 discriminant scores from predicting the unknown (archaeological/testing) datasets. A more comprehensive table that also includes all 256 training discriminant scores (from the labeled experimental dataset) is attached at the end of this study (Appendix B & C).

4.2.1 QDA Raw material Model

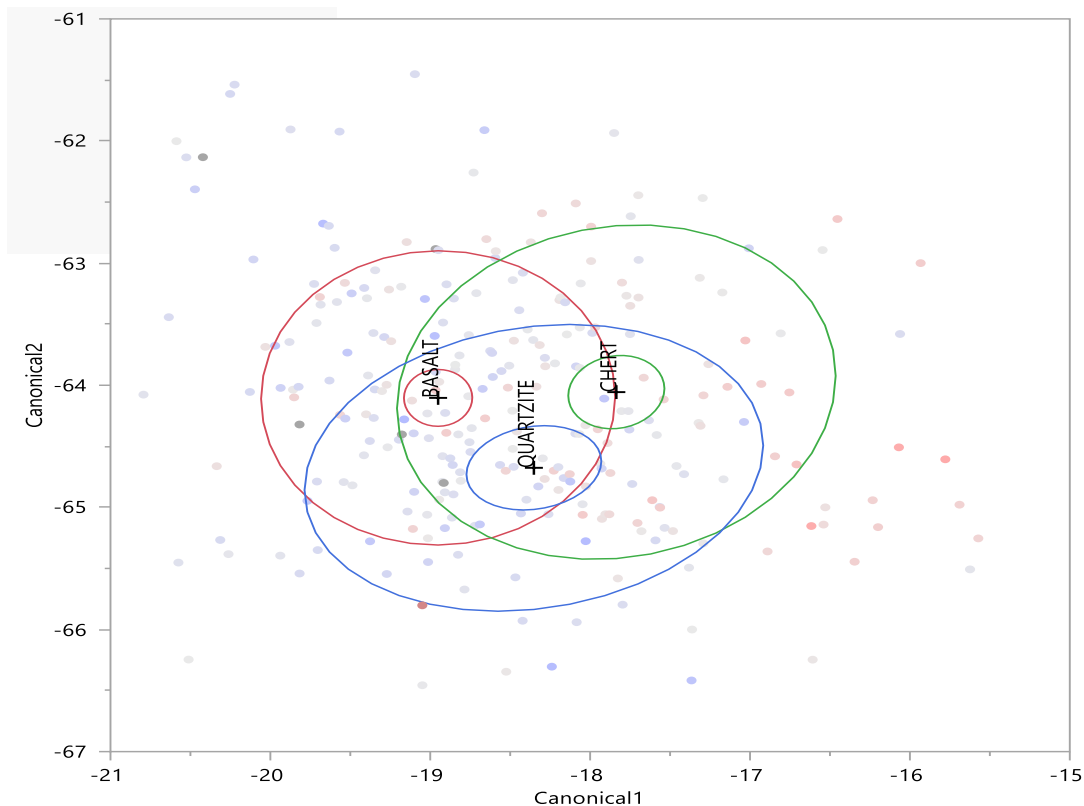


Figure 4. 2: QDA Canonical plot showing classification of raw materials

Table 4. 4: Shrinkage Details

Overall Shrinkage	Overall Lambda	RAW MATERIALS	Shrinkage	Lambda
0.97809	0.02191	BASALT	0.94355	0.05645
		CHERT	0.95823	0.04177
		QUARTZITE	0.84463	0.15537

Table 4. 5: Score Summaries (experimental or training dataset) – Raw material model

Source	Count	Number Misclassified	Percent Misclassified	Entropy Rsquare	-2LogLikelihood
Training	256	90	35.1563	0.31783	365.047

Table 4. 6: Confusion matrix – Raw material model

Actual	Predicted Count			RAW MATERIALS	Count
RAW MATERIALS	BASALT	CHERT	QUARTZITE	RAW MATERIALS	Count
LAVA	98	7	11	LAVA	116
CHERT	34	51	5	CHERT	90
QUARTZITE	23	10	17	QUARTZITE	50

Table 4. 7: Discriminant Scores (Archaeological or Testing dataset) – Raw material model

Row	Actual	Predicted	Prob (Pred)	Others
1	HEBT4_L7_232-1	LAVA	0.8915	QUARTZITE 0.11
2	HEBT4_L8_147-1	QUARTZITE	0.5114	LAVA 0.49
3	HEBT4_L8_223-1	QUARTZITE	0.7246	LAVA 0.16 CHERT 0.12
4	HEBT4_L8_294-2	LAVA	0.7848	QUARTZITE 0.21
5	HEBT4_L8_359-2	QUARTZITE	0.9020	LAVA 0.25 QUARTZITE 0.22
6	HEBT4_L8_359-2b	QUARTZITE	0.5274	LAVA 0.23 CHERT 0.24
7	HEBT4_L8_372-3a	QUARTZITE	0.5209	LAVA 0.39
8	HEBT4_L8_372-3b	QUARTZITE	0.4306	LAVA 0.40 CHERT 0.17
9	HEBT4_L8_373-2	CHERT	0.9272	LAVA 0.23 QUARTZITE 0.38
10	HEBT4_L7_195-1	LAVA	0.6092	QUARTZITE 0.37
11	HEBT4_L8_351-2	CHERT	0.9933	
12	HEBT4_L8_372-4	QUARTZITE	0.5055	LAVA 0.34 CHERT 0.16
13	HEBT4_L8_391-1	LAVA	0.9155	CHERT 0.12
14	HEBT4_L8_359-1a	LAVA	0.9219	
15	HEBT4_L8_188-1	LAVA	0.9714	
16	HEBT4_L8_232-1	LAVA	0.9558	
17	HEBT4_L8_351-1	LAVA	1.0000	
18	HEBT4_L8_372-1	LAVA	0.9839	
19	HEBT4_L8_468-2	LAVA	0.9652	
20	HEBT4_L8_359-1b	LAVA	1.0000	

The QDA raw material model classifying cut marks made by tools of different raw materials (Basalt, Chert and Quartzite) had about 65% accuracy (Table 4.4). Out of the 20 archaeological samples, 55% (11 samples) were classified as Lava (Basalt & Phonolite), with a mean posterior probability of 90%. 35% (7 archaeological samples) were classified as quartzite with a mean posterior probability of 60%, and 10% (2 archaeological samples) were classified as chert, with a mean posterior probability of about 96% (see Table 4.6).

4.2.2 QDA Technology Model

Discriminant Method:	Quadratic
Classification:	TECHNOLOGY

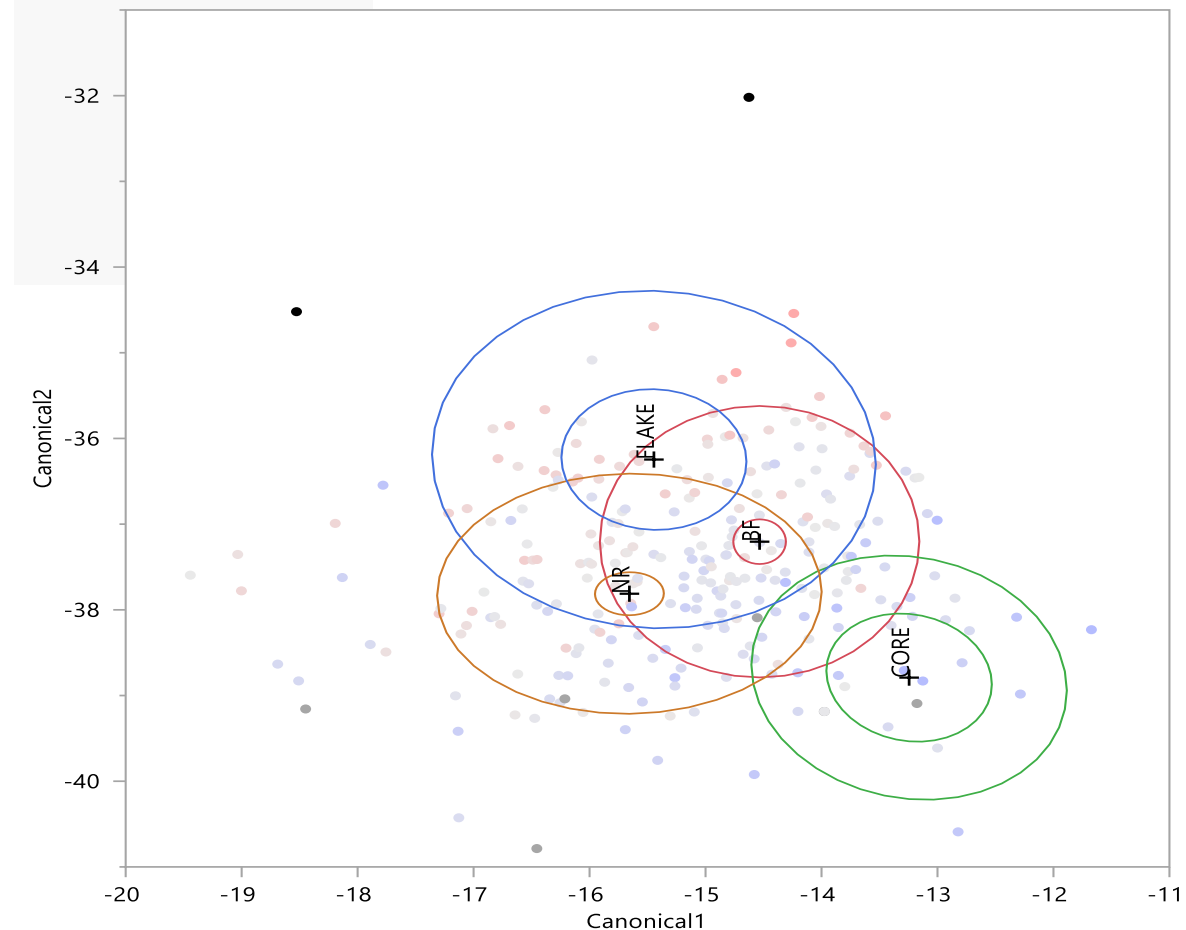


Figure 4. 3: QDA Canonical plot showing classification of technology

Table 4. 8: Score Summaries – Technology model

Source	Count	Number Misclassified	Percent Misclassified	Entropy RSquare	-2LogLikelihood
Training	256	58	22.6563	0.49763	271.617

Table 4. 9: Confusion matrix – Technology model

Actual TECHNOLOGY	Predicted Count			
	BF	CORE	FLAKE	NR
BF (Biface)	89	3	3	27
CORE	2	10	0	0
FLAKE	1	0	18	0
NR (No retouch flake)	20	1	1	81

Groups

TECHNOLOGY	Count
BF (Biface)	122
CORE	12
FLAKE	19
NR (No retouch flake)	103

Table 4. 10: Discriminant Scores (Archaeological or Testing dataset) – Technology model

Row	Actual	Predicted	Prob Others (Pred)
1	HEBT4_L7_232-1	NR	0.9992
2	HEBT4_L8_147-1	NR	0.9998
3	HEBT4_L8_223-1	BF	0.9524
4	HEBT4_L8_294-2	NR	0.6533 BF 0.35
5	HEBT4_L8_359-2	NR	0.9311
6	HEBT4_L8_359-2b	BF	0.8437 NR 0.16
7	HEBT4_L8_372-3a	NR	0.8639 BF 0.14
8	HEBT4_L8_372-3b	NR	0.9952
9	HEBT4_L8_373-2	BF	0.9001
10	HEBT4_L7_195-1	NR	0.8556 BF 0.14
11	HEBT4_L8_351-2	NR	1.0000
12	HEBT4_L8_372-4	NR	0.9999
13	HEBT4_L8_391-1	NR	0.9892
14	HEBT4_L8_359-1a	NR	0.9997
15	HEBT4_L8_188-1	NR	0.9960
16	HEBT4_L8_232-1	BF	0.6835 NR 0.32
17	HEBT4_L8_351-1	NR	0.9978
18	HEBT4_L8_372-1	NR	0.9538
19	HEBT4_L8_468-2	NR	0.9952
20	HEBT4_L8_359-1b	NR	1.0000

The QDA technology model classifying cut marks made by tools of different technologies (BF, CORE, FLAKE, and NR) had about 77% accuracy (Table 4.7). Out of the 20 archaeological samples, 80% (16 samples) were classified as NR (No retouch flake), with a mean posterior probability of 96%. On the other hand, 20% (4 archaeological samples) were classified as BF (biface) with a mean posterior probability of about 85% (see Table 4.9).

4.2.3 QDA Technology + Raw material (ALL) Model

Discriminant Method: Quadratic
 Classification: ALL (Raw material + Technology)

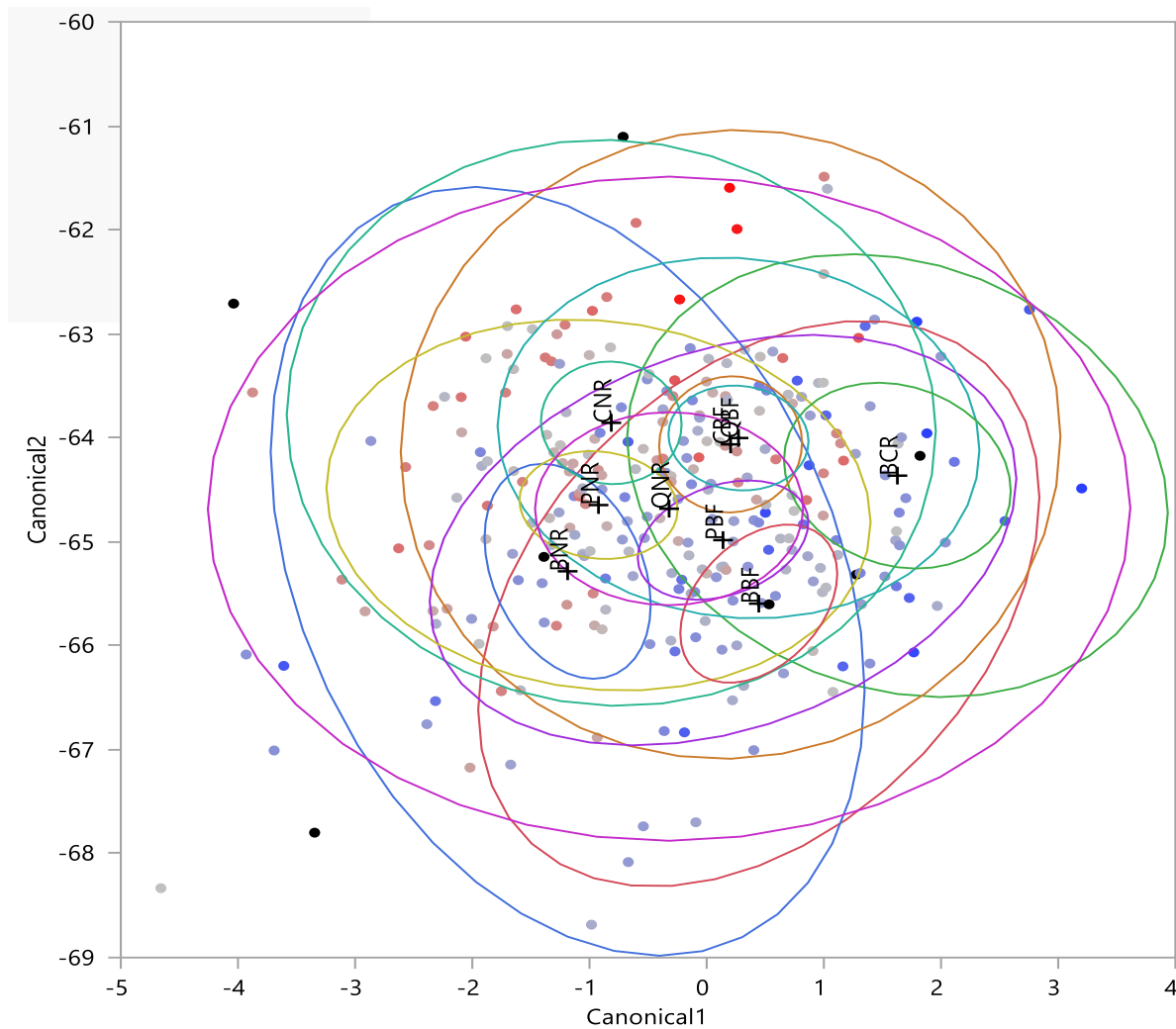


Figure 4. 4: QDA Canonical plot showing classification for both technology and raw material groups combined

Table 4. 11: Score Summaries – ALL model (raw material + technology)

Source	Count	Number Misclassified	Percent Misclassified	Entropy RSquare	-2LogLikelihood
Training	256	81	31.6406	0.58268	456.79

Table 4. 12: Confusion matrix – ALL model (raw material + technology)

Actual	Predicted Count									
ALL	BBF	BCR	BNR	CBF	CNR	PBF	PNR	QBF	QNR	
BBF	20	0	1	0	1	3	1	0	1	
BCR	0	11	0	0	0	0	0	0	1	
BNR	0	0	18	0	2	0	0	0	7	
CBF	1	1	2	22	9	1	3	1	5	
CNR	1	0	1	0	31	1	1	0	10	
PBF	0	0	1	0	2	17	1	1	3	
PNR	0	0	0	0	2	0	21	1	1	
QBF	0	2	0	0	3	0	0	14	6	
QNR	1	0	0	0	1	1	1	0	21	

Table 4. 13: Discriminant Scores - ALL model (raw material + technology).

Row	Actual	Predicted	Prob (Pred)	Others
1	HEBT4_L7_232-1	LBF	0.5491	BNR 0.45
2	HEBT4_L8_147-1	LBF	1.0000	
3	HEBT4_L8_223-1	CNR	0.8601	QBF 0.14
4	HEBT4_L8_294-2	LBF	0.9989	
5	HEBT4_L8_359-2	LBF	0.9996	
6	HEBT4_L8_359-2b	CNR	0.7972	BBF 0.19
7	HEBT4_L8_372-3a	LNR	0.3982	CBF 0.10 CNR 0.11 PNR 0.38
8	HEBT4_L8_372-3b	LNR	0.9998	
9	HEBT4_L8_373-2	CBF	0.8068	CNR 0.11
10	HEBT4_L7_195-1	CNR	0.9686	
11	HEBT4_L8_351-2	LNR	0.9139	
12	HEBT4_L8_372-4	LNR	0.5397	CBF 0.46
13	HEBT4_L8_391-1	LNR	0.9817	
14	HEBT4_L8_359-1a	LBF	0.6717	BNR 0.33
15	HEBT4_L8_188-1	LBF	1.0000	
16	HEBT4_L8_232-1	LBF	1.0000	
17	HEBT4_L8_351-1	LBF	1.0000	
18	HEBT4_L8_372-1	LBF	1.0000	
19	HEBT4_L8_468-2	LNR	0.6894	BBF 0.31
20	HEBT4_L8_359-1b	LBF	1.0000	

The final QDA model ‘ALL’ (combining raw materials + technology) classified cut marks made by tools of different technologies and raw materials classes/types; LBF (Lava Biface), LNR (Lava No retouch flake), CBF (Chert Biface), CNR (Chert No retouch flake), with 68.4% accuracy (Table 4.10). Out of the 20 archaeological samples, 50% (10 samples) were classified as LBF, with mean posterior probability of 92%. 15% (3 archaeological samples) were classified as CNR with mean probability of 88%. 30% (6 archaeological samples) were classified as LNR with a mean posterior probability of 80%. And finally, 5% (1 archaeological sample) was classified as CBF with mean posterior probability of about 81% (see Table 4.12).

4.2.3 Conflicts between models and arbitration

The three QDA models had different classification accuracies, with the combined model (technology + raw material) having the lowest classification accuracy. Following Keevil (2018), the tool raw material and technology classifications of each archaeological cut mark were recorded and compared between the tool technology only QDA model, the raw material only QDA model and technology + raw material (ALL) QDA models. Eleven of the 20 fossil marks analyzed in this thesis had agreeing raw material classifications in both the raw material only and the combined (raw material + technology) discriminant models (Table 4.13). Fossil mark technology classifications were assessed by comparing the tool classifications in the technology only model and the combinative discriminant model as well. Only nine of the 20 fossil cut marks had agreeing raw material classifications in both the raw material only and combinative discriminant models (Table 4.13). The first and second posterior probabilities of the 11 cut marks that recorded conflicting tool characteristic classifications were recorded to visualize the classification confidences of each model (Table 4.13; Table 4. 14 and Table 4. 15).

Table 4. 14: HEB Fossil trace mark classifications based on the Tool Technology Only, Raw Material Only, and Tool Technology and Raw Material (ALL) discriminant models. Bolded ID numbers indicate fossils that had differing tool technology classifications between models. Starred ID numbers indicate fossils that had differing raw material classifications between models.

ID	Skeletal Element	Cut Mark location	Raw Material only	Technology only	Raw material + Technology
HEBT4_L7_232-1	Tibia	Epiphysis	Lava	Flake	Lava Biface
HEBT4_L8_147-1*	Lumbar	Spine	Quartzite	Flake	Lava Biface
HEBT4_L8_223-1*	Femur	Midshaft	Quartzite	Biface	Chert Flake
HEBT4_L8_294-2	Radius/Ulna	Epiphysis	Lava	Flake	Lava Biface
HEBT4_L8_359-2*	Tibia	Near Epiphysis	Quartzite	Flake	Lava Biface
HEBT4_L8_359-2b*	Tibia	Near Epiphysis	Quartzite	Biface	Chert Flake
HEBT4_L8_372-3a*	Radius	Midshaft	Quartzite	Flake	Lava Flake
HEBT4_L8_372-3b*	Radius	Midshaft	Quartzite	Flake	Lava Flake
HEBT4_L8_373-2	Radius	Midshaft	Chert	Biface	Chert Biface
HEBT4_L7_195-1*	Rib	Shaft	Lava	Flake	Chert Flake
HEBT4_L8_351-2*	Long bone	Midshaft	Chert	Flake	Lava Flake
HEBT4_L8_372-4*	Radius	Midshaft	Quartzite	Flake	Lava Flake
HEBT4_L8_391-1	Long bone	Midshaft	Lava	Flake	Lava Flake
HEBT4_L8_359-1a	Tibia	Near Epiphysis	Lava	Flake	Lava Biface
HEBT4_L8_188-1	Femur	Midshaft	Lava	Flake	Lava Biface
HEBT4_L8_232-1	Femur	Midshaft	Lava	Biface	Lava Biface
HEBT4_L8_351-1	Long bone	Midshaft	Lava	Flake	Lava Biface
HEBT4_L8_372-1	Radius	Midshaft	Lava	Flake	Lava Biface
HEBT4_L8_468-2	Tibia	Midshaft	Lava	Flake	Lava Flake
HEBT4_L8_359-1b	Tibia	Near Epiphysis	Lava	Flake	Lava Biface

Table 4. 15: First posterior probabilities for the HEB cut marks that had disagreeing classifications in the technology only QDA model. Second posterior probabilities are only shown in the raw material and tool technology model when the first posterior probability is less than 95%.

ID	Technology Model		Raw Material + Technology (ALL) Model		
	Classification	1 st Posterior Probability	Classification	1 st Posterior Probability	2 nd Posterior Probability
HEBT4_L7_232-1	Flake (NR)	99%	Lava Biface (LBF)	54%	45% Lava Flake (LNR)
HEBT4_L8_147-1	Flake (NR)	99%	Lava Biface (LBF)	100%	
HEBT4_L8_223-1	Biface (BF)	95%	Chert Flake (CNR)	86%	14% Quartzite Biface
HEBT4_L8_294-2	Flake (NR)	65%	Lava Biface (LBF)	99%	
HEBT4_L8_359-2	Flake (NR)	93%	Lava Biface (LBF)	99%	
HEBT4_L8_359-2b	Biface (BF)	84%	Chert Flake (CNR)	80%	20% Lava Biface

HEBT4_L8_359-1a	Flake (NR)	99%	Lava Biface (LBF)	67%	33% Lava Flake (LNR)
HEBT4_L8_188-1	Flake (NR)	99%	Lava Biface (LBF)	100%	
HEBT4_L8_351-1	Flake (NR)	99%	Lava Biface (LBF)	100%	
HEBT4_L8_372-1	Flake (NR)	95%	Lava Biface (LBF)	100%	
HEBT4_L8_359-1b	Flake (NR)	100%	Lava Biface (LBF)	100%	

Table 4. 16: First posterior probabilities for the HEB cut marks that had disagreeing classifications in the raw material only QDA model. Second posterior probabilities are only shown in the raw material and tool technology model when the first posterior probability is less than 95%.

ID	Raw Material Model		Raw Material + Technology (ALL) Model		
	Classification	1 st Posterior Probability	Classification	1 st Posterior Probability	2 nd Posterior Probability
HEBT4_L8_147-1	Quartzite	51%	Lava Biface (LBF)	100%	
HEBT4_L8_223-1	Quartzite	72%	Chert Flake (CNR)	86%	14% Quartzite Biface
HEBT4_L8_359-2	Quartzite	90%	Lava Biface (LBF)	99%	
HEBT4_L8_359-2b	Quartzite	52%	Chert Flake (CNR)	80%	20% Lava Biface
HEBT4_L8_372-3a	Quartzite	52%	Lava Flake (LNR)	79%	10% Chert Biface 11% Chert Flake
HEBT4_L8_372-3b	Quartzite	43%	Lava Flake (LNR)	99%	
HEBT4_L7_195-1	Basalt	60%	Chert Flake (CNR)	96%	
HEBT4_L8_351-2	Chert	99%	Lava Flake (CNR)	91%	
HEBT4_L8_372-4	Quartzite	50%	Lava Flake (LNR)	54%	46% Chert Biface

Following Keevil's (2018) strategy to solve the classification conflicts across models, when the HEB cut marks reported conflicting tool characteristic classifications, between either the technology only and the combined (technology and raw material) models, or between the raw material only and the combined (technology and raw material) models; further assessment was conducted by investigating the posterior probabilities of each model. When one discriminant model reported a significantly larger first posterior probability than the other discriminant model,

the tool characteristic classification with the larger first posterior probability was deemed more accurate (Keevil, 2018, p.85). Based on this strategy, this study was able to assign the most accurate classification for all HEB cut marks (Table 4.16)

Table 4. 17: Final ESA Tool classifications (Technology + Raw material) for the 20 HEB cut marks analyzed. Cut mark classifications are based on the posterior probability data of each cut mark reported in the technology only QDA model, raw material only QDA model, and tool technology/raw material QDA model.

HEB Cut Mark	ESA Tool Classification
HEBT4_L7_232-1	Lava Flake
HEBT4_L8_147-1	Lava Biface
HEBT4_L8_223-1	Quartzite Biface
HEBT4_L8_294-2	Lava Biface
HEBT4_L8_359-2	Lava Biface
HEBT4_L8_359-2b	Quartzite Biface
HEBT4_L8_372-3a	Lava Flake
HEBT4_L8_372-3b	Lava Flake
HEBT4_L8_373-2	Biface tool (unknown raw material)
HEBT4_L7_195-1	Flake tool (unknown raw material)
HEBT4_L8_351-2	Lava Flake
HEBT4_L8_372-4	Lava Flake
HEBT4_L8_391-1	Lava Flake
HEBT4_L8_359-1a	Lava Flake
HEBT4_L8_188-1	Lava Biface
HEBT4_L8_232-1	Lava Flake
HEBT4_L8_351-1	Lava Biface
HEBT4_L8_372-1	Lava Biface
HEBT4_L8_468-2	Lava Flake
HEBT4_L8_359-1b	Lava tool (Unknown technology)

However, there were instances where archaeological cut marks reported disagreeing raw material classifications in the raw material only model and the tool technology and raw material model with similar or identical posterior probabilities in each model. For example, cut mark ID: HEBT4-L8_359-1b (Table 4.16) was classified as a flake in the technology only model, and as a biface in the combined (technology + raw material) model, with both models having 100%

posterior probabilities. Therefore, this archaeological cut mark was classified as being created by a lava tool of unknown technology type. Other misclassifications that were impossible to identify, was when archaeological cut marks were classified as being made by chert raw material types in both the raw material only model and the combined (technology + raw material) model. Since there is no evidence supporting use or presence of any chert artifact or chert raw material sources at the HEB T4 & T5 (Leakey & Roe, 1994) all cut marks classified as chert were considered to be of “unknown raw material types” despite their posterior probabilities in the models. .

CHAPTER 5 DISCUSSION

5.1 Using cut mark micromorphology to predict stone tool technology and raw material types

The importance of understanding what technology or raw material was used by hominins during butchery cannot be underestimated. The study has implications to broader aspects of hominin behavioral ecology (Blumenschine et al. 1994; Blumenschine & Pobiner, 2007) as it contributes to our understanding of strategies employed by *H. erectus* during butchery as they attempted to minimize costs of extracting the high-caloric meat resources that could fund the metabolic demands of evolving and maintaining bigger brains (Bunn, 2006; Isler & Van Schaik, 2014; Pante, 2010; Pante, 2013; Ungar, 2006). This study used optical profilometry to obtain quantitative data (cut mark measurements) that could diagnose technology and raw material types used by hominins for butchery, through statistical analyses.

5.1.1 Identifying ESA industries at HEB site from cut marks micromorphology

Classification (diagnosis) results from QDA analyses done in this study, reinforces the plausibility of Pante et al (2017) optical profilometry protocols and Keevil (2018) QDA statistical models as promising contenders for objective and replicable methods of studying BSMs. There were, however, some variations in classification accuracy levels between Keevil (2018) and this study. When identifying the archaeological cut marks (cut marks from recovered from archaeological fossils), Keevil (2018) models achieved; 71.22% accuracy in identifying raw material types (raw material only model), 78.54% accuracy in identifying technology types (technology only model), and 80.97% accuracy in identifying both raw materials and technology (combined raw material and technology model). On the other hand, this study achieved; 64.84%

accuracy when identifying raw material types (raw material only model), 77.34% accuracy when identifying technology types (technology only model), and 68.36% accuracy when identifying both raw materials and technology (combined raw material and technology model).

The variations in classification accuracy levels between the two studies is caused in part by the methodological differences when applying the statistical models. For example, unlike in Keevil (2018), this study combined Basalt and Phonolite into one classification group and shrunk the covariance matrices on JMP when classifying raw materials for better accuracy. Furthermore, cross validation protocols for this study were different from Keevil's. The study defined a 90% (training) to 10% (testing) split of the dataset for randomized cross validation on JMP. While this procedure is not explained in Keevil (2018), it's most likely that his cross-validation protocols were different from this study resulting in differences in accuracy levels of the models.

However, not every methodological difference between this study and Keevil (2018) was the cause of varying classification accuracies between the two studies. For example, the varying types of statistical softwares used to compute QDA models by both Keevil (used R statistical software) and this study (used JMP) have small or negligible influence on the results. In order to negate such suspicions, mock QDA analyses were done on both R and JMP to test if the differences in algorithmic designs for computing the QDA discriminant models (e.g. definition and inclusion of floating-point numbers, criteria for defining model accuracy levels etc.) had any influence on the results. The mock models showed a 1-3% difference in accuracy levels between the two softwares. This means that, if everything else is constant, software packages (R and JMP), should yield relatively similar results.

Furthermore, since the scanning process (measuring cut mark micromorphology) in both Keevil (2018) and this study followed Pante et al (2017) protocols, using different 3D scanners

(optical profilometers) did not affect replicability of Keevil's methods. Preliminary studies have shown that both NANOVEA ST400 (used on Keevil, 2018) and S NEOX scanners (used in this study) produced the same measurements of cut marks, with differences being on the amount of time used in the scanning process. While Nanovea ST400 scanner can take up to 1 hour to scan one cut mark (Pante et al. 2017), the new S Neox scanner only requires a few seconds or minutes to scan a cut mark. These technical differences are reflected on their prices.



Figure 5. 1: Left image is the Nanovea ST400 white light non-contact confocal profilometer used in Pante et al (2017). Right image is the S Neox non-contact 3D optical profilometer used in this study

A: Diagnosing technology types of ESA butchery tools at HEB site around 0.9Ma.

The study used Keevil's (2018) statistical discriminant models to identify and classify the relationship between cut mark micromorphology and stone tool form. The 'technology only' quadratic discriminant analysis model used in the study; classified cut mark measurements based on the technological form of the tool used to create those cut marks with 77.34% accuracy. 80% (16 samples) were classified as NR (No retouch flake), and 20% (4 archaeological samples) were

classified as BF (biface). These results are consistent with what Mary D. Leakey found during her excavations at HEB site where flake instances surpassed all other technology types (Leakey & Roe, 1994). Mary Leakey reported that, out of 303 lithic materials recovered from HEB site (level 3), a significantly large portion (n=201) of the assemblage was made up of flakes (66.3%). Bifaces made up about 33% of the assemblage (n=100), and cores made up about 0.6% (n=2) of the assemblage. In level 4, she found out that flakes made up about 72.5 % (eq. 158 specimens) of the total assemblage (n=218), followed by Bifaces – which made up about 27.5% (60 specimens) of the assemblage. At level 4, Mary Leakey did not record any core tools (see Table 5.1).

ESA technology types diagnosed from the 3D measurements of cut mark micromorphology indicates how much a certain technology type was used during butchery (to create cut marks). Results from 3D analyses done in this study, therefore, ignores all unused tools at the HEB site (regardless of their technology types), and would only count tools used for butchery (to create butchery marks). Frequency of ESA technology types discovered at HEB site (Leakey & Roe, 1995) provides a general count of tools manufactured by hominins at HEB site (whether used during butchery or not). Therefore, consistency in greater proportions of flake frequencies in both the 3D diagnoses and artifacts studies at the site, indicate that hominins at HEB made and used flakes more than other tool types.

Reasons for flakes preference over bifaces at HEB can be inferred from actualistic butchery experiments, which have been instrumental in demonstrating technological efficacy of different ESA tools (Jones, 1980;1981; Key & Lycett, 2017; Key et al. 2020). The most obvious advantage of flake tools is that it takes a significantly shorter time and less complicated process to make them in comparison to the biface handaxes. This is very advantageous in a highly competitive environment where meat extraction from carcasses must be done faster. Furthermore, studies have

demonstrated flake tools to be significantly more efficient than handaxes when undertaking relatively small, precise cutting tasks (Key & Lycett, 2017). Based on this, scientists have argued that bifaces were probably used on special cases as a requirement to undertake specific type of tasks (when cutting relatively large and resistant portions of carcasses), rather than them being inherently superior to flakes in all cutting tasks (Key & Lycett, 2017).

B: Diagnosing raw material types of ESA butchery tools at HEB site around 0.9Ma.

The QDA raw material model classifying cut marks made by tools of different raw materials (Basalt, Chert and Quartzite), classified 55% of the tested archaeological sample from HEB site as Basalt, 35% were identified as quartzite, and 10% as chert. Unlike results from technology model discussed above, the frequency and proportion of the raw material types diagnosed from the 3D studies of cut mark micromorphology are not consistent with the artifact distribution at the HEB site. Mary D. Leakey's excavation at HEB site (Leakey & Roe, 1994) recorded that, out of the 905 lithic materials recovered from HEB site (level 3), significantly large portions of the assemblage were made up of quartzite (63.5%) and Lava (31.9%). Also, in level 4, she found out that Quartzite made up 81.4% (eq. 903 specimens) of the total assemblage (n=1110), followed by Lava (Basalt & Phonolite) – which made up 14.2% (158 specimens) of the assemblage. This pattern suggests that, at HEB hominins used more lava-made tools during butchery (as diagnosed from 3D studies of cut mark micromorphology) despite quartzite tools being the most available (abundant) at the site (Leakey & Roe, 1994).

Such a pattern is interesting because our common understanding is that, relative abundance and total mass of lithic artifacts made from different materials, can be used an indicator of both; availability of those raw materials, and hominin preferences for those specific raw materials (Leakey, 1966; McHenry & de la Torre, 2018). Butchery actualistic studies (Jones, 1979; Key et

al. 2020) show that both lava (basalt) and quartzite have advantageous ‘butchery properties’ over other raw material types. For example, basalt (lava) has a strong, durable cutting edge, and therefore can be used to create tools that last longer (durable) during butchery (Jones, 1979; Key et al. 2020), whereas, quartzite has the sharpest cutting edge, making it ideal for creating sharp butchery tools (Key et al. 2020). Based on this, it is impossible to use functional/practical attributes of these materials as an explanation for the preferential use of lava tools over the abundant quartzite tools at HEB site.

An alternative explanation would be looking at relative availability of raw material sources, where the distance of the raw material primary sources from the butchery site, can also influence raw material type usage and preferences (McHenry & de la Torre, 2018). Similar to effects of paleoclimate changes in Africa which led to patchiness of food and water resources, lithic tools raw material distributions across Olduvai would have subjected HEB hominins to landscape and predatory pressures associated with exploitation of resources that were widely distributed across the Olduvai Pleistocene landscape (Cachel et al. 1998; Leakey, 1966; McHenry & de la Torre, 2018; Santonja et al. 2014). This means that there would be conscious (budgeted) usage of raw material types depending on their availability (McHenry & de la Torre, 2018; Santonja et al. 2014).

At HEB site, primary source of quartzite raw material is located 15kms from the site (Enabor Soit hill), whereas, lava raw material types are further away, at least 19km (Lemagrut) and 22km (Engelosin). Although such proximity of quartzite primary source can explain abundance of quartzite tools at HEB, Researchers (Leakey & Roe, 1994; Njau et al. 2020) have also described HEB stratigraphy as comprising of alternating horizons of claystones and siltstones with occasional sandy, pebbly stream fill and lag deposits. These sedimentological properties are suggestive of shifting lake and stream positions, resulting from regionally driven

palaeoenvironmental change (Njau et al. 2020, p.3). The riverine and lacustrine contexts are evidence of a stream running through HEB and draining into the Olduvai paleolake (Njau et al. 2020). This stream probably acted as a secondary raw material source, transporting lava from surrounding volcanic mountains. Presence of a stream transporting lava through HEB would make lava the most accessible raw material at HEB (proximity-wise) which can be used without budgetary constraints, whereas, quartzite would have been manufactured, but used sparingly accounting for the 19km distance from the source.

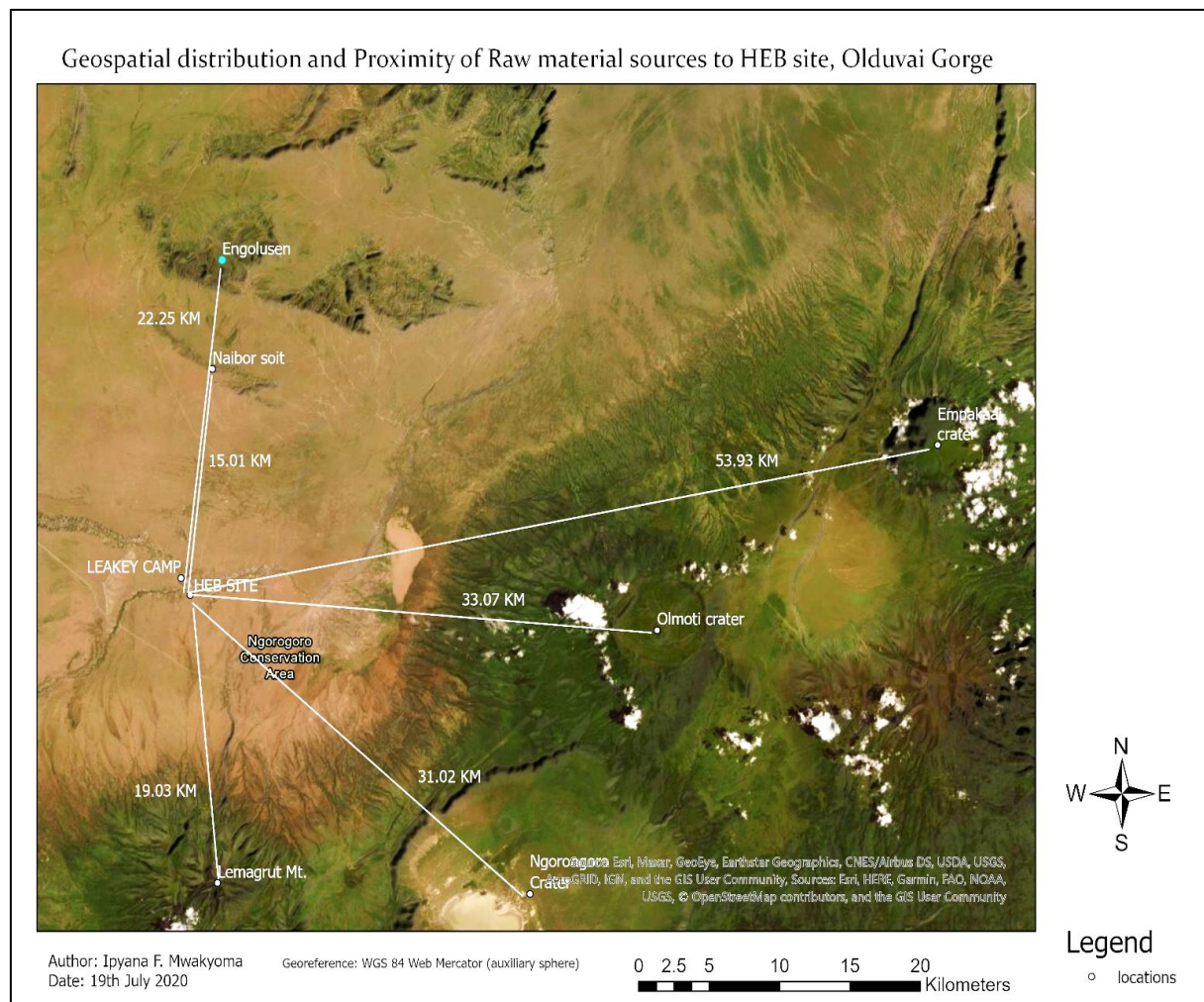


Figure 5. 2: GIS satellite image showing the spatial distribution and proximity of raw material sources from HEB site, Olduvai Gorge.

C: Diagnosing both raw material and technology types of ESA butchery tools at HEB

Quadratic discriminant analysis of cut mark measurements based on similarities in both the raw material and technological form of the tool that made those cut marks, classified cut marks with 68% accuracy. Keevil (2018) assessed that cut marks made by stone tools of the same technological form are more likely to preserve similar micromorphological features than cut marks made by tools of the same raw material type and that tool technological form influences cut mark morphology more than tool raw material type (p.93). This explains the varying accuracy levels and classification conflicts between the technology only, raw material only, and the combined (technology + raw material) models.

Out of the 20 archaeological samples from HEB, the combined (technology + raw material) model had identified 9 tools (45%) as lava flakes, 6 tools (30%) as lava bifaces, 2 tools (10%) as Quartzite Bifaces, 1 tool (5%) as a biface of unknown raw material, 1 tool (5%) as a flake of unknown raw, and 1 tool (5%) as a lava tool of unknown technology. This means that there are 10 (50%) flakes tools (regardless of their raw material types) and 9 (45%) bifaces (regardless of their raw material types). Though on a relatively lower margin, the combined (technology + raw material) model agrees with the ‘technology only’ model that more flake tools were used for butchery at HEB compared to bifaces. The combined (technology + raw material) model also agrees with the ‘raw material only’ model that tools made of lava were used more during butchery than other raw material types by classifying 16 tools (80%) of all cut marks as being created by lava tools (irrespective of their technology types). The rest were diagnosed as being created by quartzite tools (10%) and an unidentified/inconclusive raw material type (10%).

The combined (technology + raw material) classification also indicated several butchery behaviors including using the same tool multiple times to process a single carcass element.

Evidence for such behavior has been reported by researchers before including Keevil (2018), who reported a single tool being used to create four different cut mark traces on the same fossil bone element. In this study as well, three different cut marks located on midshaft section of a radius and positioned close and parallel to each other (HEBT4_L8_372-3a, HEBT4_L8_372-3a, and HEBT4_L8_372-4) were all diagnosed as being created by lava flake tool. Adjacent to these cut marks but on the same bone element, another cut mark was diagnosed as being created by lava biface tool (HEBT4_L8_372-1). Keevil (2018) proposed that, such pattern could have been created by either a butcher using a single tool multiple times to process a single carcass element, or a butcher or multiple butchers using several tools of the same form to process a single carcass element (p. 98). However, improving credibility of these assumptions would require 3D analysis of cut marks created by controlled actualistic studies focusing on butchery sequences, coupled with studies of macroscopic cut mark patterns on bones.

5.3 Limitation of the study and Future research prospects/direction

5.3.1 Limitations of the study

The study relied on the ability of discriminant models to classify cut mark micro-morphometrics into specific tools types. However, the accuracy levels achieved by the discriminant models were average, and low compared to Keevil (2018) or other BSM discriminant studies using 3D methods (e.g. Pante et al. 2017). Efforts to achieve better classification accuracies were hampered by many factors, notably size of the sample dataset. The discriminant models in the study had a small sample size (n=276), which is relatively inadequate to train a statistical classifier.

Furthermore, the archaeological sample under study was also very small (n=20), which might limit the study's ability to accurately represent the whole HEB site. The archaeological sample

was selected based on subjective criteria related to the state of cut mark preservation, therefore, interpretations made in the study could only be representative of a subset of butchery activities at HEB rather than the entirety of hominin butchery behavior at the site.

Also, the training dataset from (Keevil, 2018) was created in a controlled experiment that was designed to keep subjective butchery attributes constant by using a mechanized saw to create the cut marks. This means that subjective aspects of butchery activity, such as how tools were held during butchery, or the amount of force applied when defleshing the carcass were not considered when creating the training dataset used in the study. While this method is commendable for reducing bias and subjectivity, it does not truly reflect an actual butchery event that took place at HEB site, where different butchers probably held butchery tools differently, or applied different amount of force when defleshing a carcasses to create the archaeological cut marks (testing dataset) classified in this study. Even a single butcher can hold tools differently or use different amounts of force for every separate slashing event when processing a single carcass. How tools are held, and the force applied can influence cut mark micromorphological features like the angle and depth of the cut mark, all of which were included as important variables in this study's QDA classifiers.

Other challenges were related to 3D scanning archaeological specimens. For example, the dark coloration of fossilized bones affected visibility and light reflectance, which are crucial when using the optical profilometry. Dark color absorbs light, which can obstruct photographic visibility of the mark, leading to loss of data and lowering of the quality of 3-D cut mark models.

Also, the data used in this study regarding the frequency and distribution of ESA artifacts at HEB site, came from decades' old excavation records by Leakey & Roe (1994). While Leakey's accounts were useful, they were not from the same archaeological levels as the OGCP cut marks analyzed in this study. The OGCP have recovered more than 2500 artifacts from T4 & T5, that are

directly associated and more contextually related to the archaeological cut marks used in this study. However, these artifacts have not yet been analyzed (Njau et al. 2020), and therefore could not be used in the study.

5.3.2 Future research prospects and direction

Based on the limitations of the study and results obtained, there are a lot of areas that needs improvement and further investigations. Methodologically, optical profilometry has the potential to develop into a more reliable quantitative method for studying BSMs. Its potential in diagnosing tool effector from trace marks, can be applied to taphonomic studies of fossil assemblages in sites where there are no artifacts found like Dikika, Ethiopia (McPherron et al. 2010). To achieve this, there is a need for further inter-analyst studies dedicated at improving optical profilometry measurement and analysis protocols (Pante et al. 2017). Creation of bigger cut mark database from controlled butchery experiments will further improve accuracies of the classification models used in 3D studies of cut marks.

Finally, since the research at HEB by OGCP (Olduvai Gorge Coring Project) is still on going, then, there is hope for better resolution of the interpretations made in this study by increasing the archaeological sample size. Independent analyses of the lithic artifacts recovered from HEB by OGCP, will further inform this and/or similar studies, and help build a comprehensive picture of *Homo erectus* butchery practices at HEB.

CHAPTER 6 CONCLUSION

This study identifies the technology and raw material types of the early stone age (ESA) tools used by *H. erectus* for butchery at HEB site, Olduvai gorge, around 0.9 million years ago. The study expands upon previous BSM research on hominin feeding behavior by successfully applying the quadratic discriminant analysis (QDA) models developed by Keevil (2018). Results show that, *H. erectus* used both flakes and bifaces (hand axes) to butcher animals at HEB site. Also, the QDA model diagnosing raw material types, indicate that *H. erectus* preferably used lava (basalt and phonolite) tools for butchery, despite abundance of quartzite tools at the site. These results have implications on our understanding of *H. erectus* feeding behavior at HEB site, and how the preferential use of ESA tools influenced human evolution during the Pleistocene.

The study contributes to the body of knowledge on objective and quantifiable taphonomic methods of studying BSMs. This is because apart from being able to characterize the ESA tools used for butchery by *H. erectus* at HEB, the study also demonstrated the efficacy and replicability of the optical profilometry as a method for studying cut marks. This is important, because developing an objective and standardized method of studying BSMs, provides a platform for not only, making better assumptions about our past, but also the ability to scientifically test them.

This research demonstrated that 3D optical profilometric study of butchery marks at HEB indicate hominin tool use and choice, and that the tool frequencies diagnosed from the 3D optical profilometric study, are reflective of the technology and raw material distribution at HEB site. All technology QDA models classifying 3D cut mark micromorphological measurements obtained through optical profilometry indicate that hominins at HEB used flakes more than bifaces during

butchery. This pattern is attributed to functional efficacy of flake in undertaking relatively small, precise cutting tasks (Key & Lycett, 2017). Biface tools were also used at HEB, probably to undertake specific type of tasks involving cutting relatively large and resistant portions of carcasses. This assessment is also supported by the proportional abundance of flake tools at HEB compared to bifaces (Leahey & Roe, 1994).

In terms of raw materials, QDA classification of 3D cut mark micro-morphometrics was not consistent with the known (Leahey & Roe, 1994) frequency and distribution of raw material types at HEB site. While QDA classification of HEB fossil cut mark micromorphology indicates that lava tools were mostly used to create those cut marks; it is quartzite tools and not lava, that made up the majority of stone tool artifacts recovered at HEB. This means that despite abundance of quartzite tools at HEB, hominins preferably used more lava tools during butchery. Raw material budgeting in relation to availability (proximity of raw material sources from HEB) can best explain this pattern. Sedimentological records (Leahey & Roe, 1994; Njau et al. 2020) indicates presence of a stream that probably acted as a secondary source of raw material, transporting lava from nearby volcanic mountains through HEB site. This means that there would be conscious (budgeted) usage of raw material types depending on their availability, and therefore lava (the most available) would be used more, while quartzite tools manufactured at the site would be used sparingly.

These findings have several implications in human evolution studies as characteristics of butchery tools and underlying choices on how they are used during butchery, is important in understanding how hominins mitigated costs of acquiring the high-caloric meat resources. In human evolutionary studies, meat in the diet of hominins is significant because it provided high nutritional returns (high energy/protein with low digestive costs) (Bunn, 2006; Pante, 2010; Pante,

2013; Ungar, 2006). However, this energetic advantage was usually kept in check by other factors such as the ‘costs’ of searching or acquiring and butchering that meat resource (Blumenschine & Pobiner, 2007; Shipman & Walker, 1989). This study contributes to our understanding of how hominin butchery behavior was instrumental in the acquisition and maximization of the metabolic advantages associated with meat diet (e.g. funding the evolution, and maintenance of a bigger brain).

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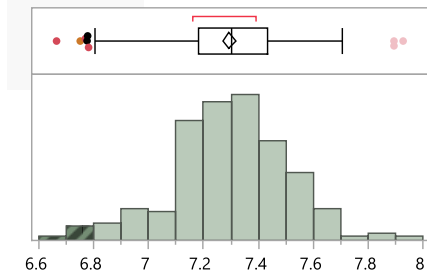
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APPENDIX A - RAW MEASUREMENTS FROM ARCHAEOLOGICAL CUT MARKS

ID	SURFACE (3D)	VOLUME (3D)	MAX DEPTH (3D)	MEAN DEPTH (3D)	MAX LENGTH (3D)	MAX WIDTH (3D)	MAX DEPTH (PRFD)	AREA (PRFD)	WIDTH (PRFD)	RA (PRFD)	WA (PRFD)	ANGLE (PRFD)	RADIUS (PRFD)
T4_L7_195-1	300183	5834020	47.1881	19.4349	2539.55	111.749	35.8637	2528.92	115.92	0.294518	7.74718	110.008	62.28
T4_L7_232-1	474588	13782648	74.7634	29.0413	7640.98	118.895	35.8055	2135.87	126.96	0.414595	10.1616	108.971	64.1616
T4_L8_147-1	1087062	45668936	93.4347	42.0113	6095.1	152.852	27.497	1879.97	121.44	0.276911	6.38159	127.587	75.1457
T4_L8_188-1	1565843	49729211	67.4741	31.7587	8435.95	157.321	17.0053	1858.7	190.44	0.544015	2.46493	157.145	255.435
T4_L8_223-1	816188	30237068	85.7362	37.0467	3508.63	348.606	62.0964	12687.6	339.48	0.738591	12.3852	135.889	277.298
T4_L8_232-1	602320	18273256	65.6348	30.3381	3849.657	302.037	20.6981	3904.69	303.6	0.564427	8.61632	166.817	786.603
T4_L8_294-2	1643627	53009116	99.7602	32.2513	11973.73	391.364	36.0956	6312.76	320.16	0.877583	7.12864	154.059	377.918
T4_L8_351-1	192394	2100125	30.8955	10.9158	1928.99	149.236	7.24122	470.976	118.68	0.0823033	1.76134	163.068	346.759
T4_L8_351-2	186445	5050305	48.4657	27.0874	2281.32	42.5574	26.8265	1809.04	179.4	2.05597	5.04801	145.203	212.813
T4_L8_359-1a	119231	5163297	81.8146	43.3051	1937.13	104.545	25.2297	1245.68	96.6	0.385071	5.7554	124.263	58.8
T4_L8_359-1b	150771	6699224	71.565	44.433	1600.81	131.129	6.0788	277.968	74.52	0.167872	0.814142	158.951	207.993
T4_L8_359-2	1248612	105938389	138.601	84.8449	7546.16	261.971	56.8211	9608.18	336.72	1.45812	15.7521	138.991	342.403
T4_L8_359-2b	1508529	56691582	77.4564	37.5807	7726.51	264.026	54.5429	8127.38	267.72	1.35748	10.5876	133.242	185.131
T4_L8_372-1	359608	6167786	47.5549	17.1514	2909.76	149.969	14.6919	1293.83	129.72	0.157227	2.90791	151.979	144.831
T4_L8_372-3a	1480728	44085766	88.9944	29.773	9829.04	180.036	52.6124	7396.3	273.24	1.17628	9.85654	133.829	193.533
T4_L8_372-3b	761257	16156721	60.2608	21.2237	10140.961	135.649	39.2008	3822	195.96	2.03186	5.51971	136.111	144.656
T4_L8_372-4	552798	8352982	45.7256	15.1104	6598.82	93.8606	29.9489	3376.02	231.84	1.05802	5.0888	148.234	229.731
T4_L8_373-2	1821920	57638743	137.52	31.6363	11346.1	382.974	111.918	44159.3	687.24	3.26785	14.5313	144.809	634.465
T4_L8_391-1	469328	14447206	60.8351	30.7828	5626.39	111.885	29.2453	2389.84	154.56	0.418201	6.25504	137.542	117.499
T4_L8_468-2	120084	1142406	26.8369	9.5134	1925.529	93.9714	13.2971	933.88	118.68	0.458641	3.09233	160.019	185.845

APPENDIX B – DISTRIBUTIONS OF ALL 12 INDIVIDUAL NUMERIC VARIABLES FROM A JOINT EXPERIMENTAL & ARCHAEOLOGICAL DATASET TABLE

SA distribution



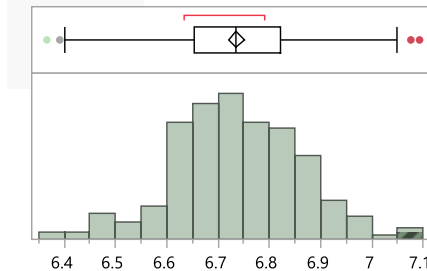
Quantile

100.0 %	maximum	7.927204268
99.5%		7.9147131526
97.5%		7.6418541046
90.0%		7.5573253895
75.0%	quartile	7.435424376
50.0%	median	7.3026589265
25.0%	quartile	7.182044099
10.0%		7.030748901
2.5%		6.8005231753
0.5%		6.6974797975
0.0%	minimum	6.665170075

Summary statistics

Mean	7.2947029
Std Dev	0.2074181
Std Err Mean	0.0125306
Upper 95% Mean	7.3193718
Lower 95% Mean	7.270034
N	274

Volume distribution



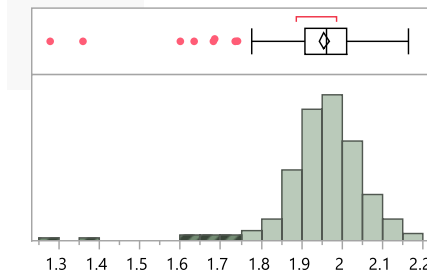
Quantile

100.0 %	maximum	7.093108118
99.5%		7.0867420381
97.5%		6.973345031
90.0%		6.8822455975
75.0%	quartile	6.8222655423
50.0%	median	6.734887987
25.0%	quartile	6.6533830963
10.0%		6.5990371905
2.5%		6.4647655863
0.5%		6.3755230659
0.0%	minimum	6.366105653

Summary statistics

Mean	6.7357912
Std Dev	0.1233461
Std Err Mean	0.0074516
Upper 95% Mean	6.7504611
Lower 95% Mean	6.7211213
N	274

MDP distribution



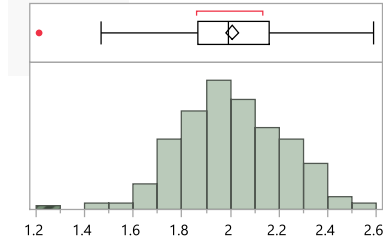
Quantile

100.0 %	maximum	2.165598913
99.5%		2.1620712419
97.5%		2.1293000016
90.0%		2.061756924
75.0%	quartile	2.0122597893
50.0%	median	1.96008517
25.0%	quartile	1.9065134755
10.0%		1.8619383225
2.5%		1.7293738
0.5%		1.3088534336
0.0%	minimum	1.278462567

Summary statistics

Mean	1.9555624
Std Dev	0.1014617
Std Err Mean	0.0061295
Upper 95% Mean	1.9676296
Lower 95% Mean	1.9434953
N	274

MEAN distribution



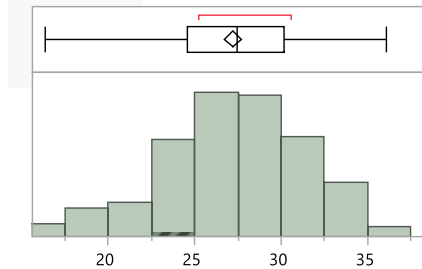
Quantile

100.0 %	maximum	2.589813214
99.5%		2.5770576779
97.5%		2.4013895318
90.0%		2.2959868695
75.0%	quartile	2.1567632235
50.0%	median	1.992657188
25.0%	quartile	1.8641258063
10.0%		1.746029881
2.5%		1.6126152116
0.5%		1.3085482783
0.0%	minimum	1.213010387

Summary statistics

Mean	2.0061532
Std Dev	0.2114941
Std Err Mean	0.0127768
Upper 95% Mean	2.0313068
Lower 95% Mean	1.9809996
N	274

ML distribution



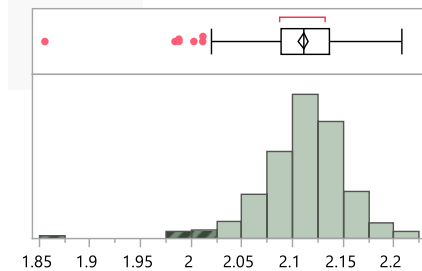
Quantile

100.0 %	maximum	36.12087072
99.5%		35.998929908
97.5%		34.50304812
90.0%		32.736764805
75.0%	quartile	30.207791973
50.0%	median	27.478374255
25.0%	quartile	24.565225998
10.0%		21.74853287
2.5%		17.958831068
0.5%		16.332482608
0.0%	minimum	16.33110239

Summary statistics

Mean	27.205057
Std Dev	4.144373
Std Err Mean	0.2503707
Upper 95% Mean	27.69796
Lower 95% Mean	26.712154
N	274

MW distribution



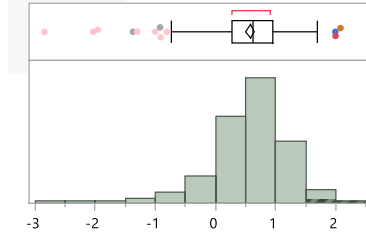
Quantile

100.0 %	maximum	2.20839956
99.5%		2.2065978001
97.5%		2.1814980628
90.0%		2.1566131235
75.0%	quartile	2.1369164178
50.0%	median	2.1114713915
25.0%	quartile	2.0891518838
10.0%		2.0624070785
2.5%		2.011501999
0.5%		1.9037010199
0.0%	minimum	1.855543671

Summary statistics

Mean	2.1106702
Std Dev	0.0412742
Std Err Mean	0.0024935
Upper 95% Mean	2.1155791
Lower 95% Mean	2.1057614
N	274

RA distribution



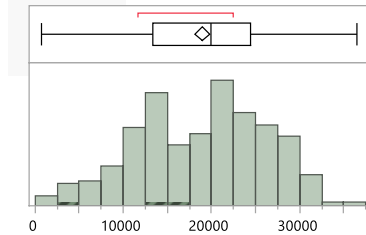
Quantile

100.0 %	maximum	2.078824893
99.5%		2.0479172239
97.5%		1.6508587136
90.0%		1.246207736
75.0%	quartile	0.9501861933
50.0%	median	0.6315135765
25.0%	quartile	0.270034122
10.0%		-0.118695424
2.5%		-0.931483718
0.5%		-2.542247909
0.0%	minimum	-2.845509951

Summary statistics

Mean	0.5755458
Std Dev	0.6349462
Std Err Mean	0.0383585
Upper 95% Mean	0.6510619
Lower 95% Mean	0.5000297
N	274

ANG distribution



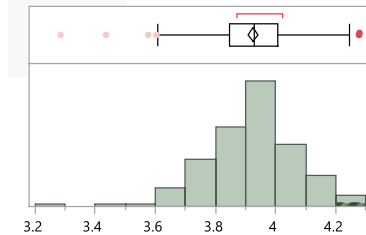
Quantile

100.0 %	maximum	36430.34266
99.5%		35413.180345
97.5%		31646.424866
90.0%		28586.06684
75.0%	quartile	24423.56272
50.0%	median	19880.96859
25.0%	quartile	13286.200535
10.0%		9352.3097705
2.5%		4061.366876
0.5%		1134.4837346
0.0%	minimum	719.9908115

Summary statistics

Mean	18954.66
Std Dev	7304.0657
Std Err Mean	441.25474
Upper 95% Mean	19823.354
Lower 95% Mean	18085.965
N	274

AREA distribution



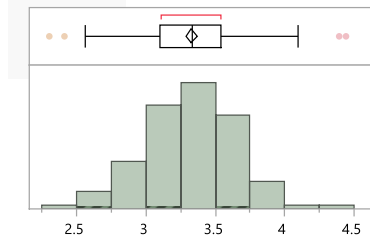
Quantile

100.0 %	maximum	4.278973665
99.5%		4.2783868669
97.5%		4.2149559905
90.0%		4.1075069515
75.0%	quartile	4.0060925795
50.0%	median	3.927404787
25.0%	quartile	3.8452828963
10.0%		3.741784958
2.5%		3.6383763706
0.5%		3.3413576521
0.0%	minimum	3.284687429

Summary statistics

Mean	3.924102
Std Dev	0.1408296
Std Err Mean	0.0085078
Upper 95% Mean	3.9408513
Lower 95% Mean	3.9073527
N	274

RAD distribution



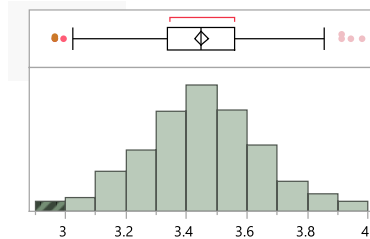
Quantile

100.0 %	maximum	4.441409655
99.5%		4.4230030946
97.5%		3.9417285155
90.0%		3.7335255575
75.0%	quartile	3.5372445083
50.0%	median	3.3353395555
25.0%	quartile	3.1036234153
10.0%		2.898753575
2.5%		2.6354152594
0.5%		2.342211411
0.0%	minimum	2.301245247

Summary statistics

Mean	3.3253174
Std Dev	0.3330523
Std Err Mean	0.0201204
Upper 95% Mean	3.3649284
Lower 95% Mean	3.2857065
N	274

W distribution



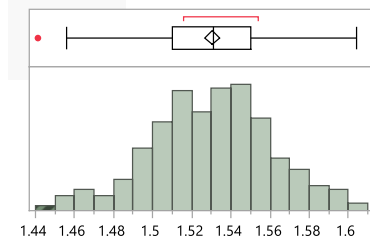
Quantile

100.0 %	maximum	3.980552648
99.5%		3.966635984
97.5%		3.8469622165
90.0%		3.689675958
75.0%	quartile	3.5589827438
50.0%	median	3.447836328
25.0%	quartile	3.3387415943
10.0%		3.193159666
2.5%		3.053129072
0.5%		2.964667834
0.0%	minimum	2.964667834

Summary statistics

Mean	3.4489501
Std Dev	0.1917598
Std Err Mean	0.0115846
Upper 95% Mean	3.4717567
Lower 95% Mean	3.4261435
N	274

MD distribution



Quantile

100.0 %	maximum	1.603917507
99.5%		1.603213686
97.5%		1.5933913284
90.0%		1.5698896335
75.0%	quartile	1.550394012
50.0%	median	1.530867138
25.0%	quartile	1.5099545538
10.0%		1.4929516605
2.5%		1.4624389778
0.5%		1.4469688054
0.0%	minimum	1.441356474

Summary statistics

Mean	1.5304207
Std Dev	0.0305904
Std Err Mean	0.001848
Upper 95% Mean	1.5340589
Lower 95% Mean	1.5267825
N	274

APPENDIX C – DISCRIMINANT SCORES OF THE QDA MODEL FOR RAW MATERIAL CLASSIFICATION

Row	Actual	Predicted	Prob Others (Pred)
1	HEBT4_L7_232-1	BASALT	0.8915 QUARTZITE 0.11
2	HEBT4_L8_147-1	QUARTZITE	0.5114 BASALT 0.49
3	HEBT4_L8_223-1	QUARTZITE	0.7246 BASALT 0.16 CHERT 0.12
4	HEBT4_L8_294-2	BASALT	0.7848 QUARTZITE 0.21
5	HEBT4_L8_359-2	QUARTZITE	0.9020 BASALT 0.25 QUARTZITE 0.22
6	HEBT4_L8_359-2b	QUARTZITE	0.5274 BASALT 0.23 CHERT 0.24
7	HEBT4_L8_372-3a	QUARTZITE	0.5209 BASALT 0.39
8	HEBT4_L8_372-3b	QUARTZITE	0.4306 BASALT 0.40 CHERT 0.17
9	HEBT4_L8_373-2	CHERT	0.9272 BASALT 0.23 QUARTZITE 0.38
10	HEBT4_L7_195-1	BASALT	0.6092 QUARTZITE 0.37
11	HEBT4_L8_351-2	CHERT	0.9933
12	HEBT4_L8_372-4	QUARTZITE	0.5055 BASALT 0.34 CHERT 0.16
13	HEBT4_L8_391-1	BASALT	0.9155 CHERT 0.12
14	HEBT4_L8_359-1a	BASALT	0.9219
15	HEBT4_L8_188-1	BASALT	0.9714
16	HEBT4_L8_232-1	BASALT	0.9558
17	HEBT4_L8_351-1	BASALT	1.0000
18	HEBT4_L8_372-1	BASALT	0.9839
19	HEBT4_L8_468-2	BASALT	0.9652
20	HEBT4_L8_359-1b	BASALT	1.0000
21	QUARTZITE	CHERT	0.6492 BASALT 0.17 CHERT 0.39
22	QUARTZITE	QUARTZITE	0.5471 BASALT 0.24 CHERT 0.21
23	QUARTZITE	QUARTZITE	0.7192 BASALT 0.16 CHERT 0.12
24	QUARTZITE	BASALT	0.6280 CHERT 0.17
25	QUARTZITE	QUARTZITE	0.6843 BASALT 0.31
26	QUARTZITE	BASALT	0.4969 CHERT 0.21
27	QUARTZITE	CHERT	0.6950 BASALT 0.13
28	QUARTZITE	CHERT	0.5949 BASALT 0.35
29	QUARTZITE	QUARTZITE	0.4548 BASALT 0.34 CHERT 0.21
30	QUARTZITE	QUARTZITE	0.5488 BASALT 0.16 CHERT 0.29
31	QUARTZITE	CHERT	0.4776 BASALT 0.24
32	QUARTZITE	QUARTZITE	0.5129 BASALT 0.12 CHERT 0.37
33	QUARTZITE	CHERT	0.5212 BASALT 0.11
34	QUARTZITE	BASALT	0.4057 CHERT 0.23
35	QUARTZITE	QUARTZITE	0.5603 BASALT 0.24 CHERT 0.20
36	QUARTZITE	CHERT	0.5701 BASALT 0.16
37	QUARTZITE	CHERT	0.4657 BASALT 0.29
38	QUARTZITE	QUARTZITE	0.4195 BASALT 0.21 CHERT 0.37
39	QUARTZITE	QUARTZITE	0.3926 BASALT 0.22 CHERT 0.38
40	QUARTZITE	BASALT	0.3950 CHERT 0.22
41	QUARTZITE	BASALT	0.5099 CHERT 0.24
42	QUARTZITE	BASALT	0.7038 CHERT 0.10
43	QUARTZITE	BASALT	0.7323 CHERT 0.11
44	QUARTZITE	BASALT	0.5604 BASALT 0.37 CHERT 0.19
45	QUARTZITE	BASALT	0.5333 CHERT 0.24

Row	Actual	Predicted	Prob Others (Pred)
46	QUARTZITE	QUARTZITE	0.6780 BASALT 0.29
47	QUARTZITE	QUARTZITE	0.8725 BASALT 0.37 CHERT 0.13
48	QUARTZITE	CHERT	0.5762 CHERT 0.26
49	QUARTZITE	QUARTZITE	0.8298 CHERT 0.15
50	QUARTZITE	QUARTZITE	0.8192 CHERT 0.13
51	QUARTZITE	QUARTZITE	0.8790 CHERT 0.11
52	QUARTZITE	CHERT	0.6671 CHERT 0.38
53	QUARTZITE	QUARTZITE	0.6420 CHERT 0.35
54	QUARTZITE	CHERT	0.8425
55	QUARTZITE	BASALT	0.4954 CHERT 0.14
56	QUARTZITE	BASALT	0.6630 CHERT 0.16
57	QUARTZITE	BASALT	0.5979
58	QUARTZITE	BASALT	0.5410 CHERT 0.36
59	QUARTZITE	BASALT	0.5078 CHERT 0.18
60	QUARTZITE	BASALT	0.5406 CHERT 0.37
61	QUARTZITE	BASALT	0.6329 CHERT 0.17
62	QUARTZITE	BASALT	0.6955 CHERT 0.11
63	QUARTZITE	BASALT	0.5193 CHERT 0.10
64	QUARTZITE	BASALT	0.6682 CHERT 0.16
65	QUARTZITE	QUARTZITE	0.6093 BASALT 0.19 CHERT 0.20
66	QUARTZITE	BASALT	0.7249 CHERT 0.15
67	QUARTZITE	BASALT	0.6065 CHERT 0.14
68	QUARTZITE	BASALT	0.5244 CHERT 0.15
69	BASALT	BASALT	0.8559 CHERT 0.12
70	BASALT	BASALT	0.6593 QUARTZITE 0.26
71	BASALT	BASALT	0.7056 CHERT 0.24
72	BASALT	BASALT	0.8616 CHERT 0.16 QUARTZITE 0.17
73	BASALT	BASALT	0.9255 CHERT 0.13 QUARTZITE 0.21
74	BASALT	BASALT	0.8817 CHERT 0.12 QUARTZITE 0.14
75	BASALT	BASALT	0.7247 CHERT 0.12 QUARTZITE 0.15
76	BASALT	BASALT	0.6595 CHERT 0.14 QUARTZITE 0.20
77	BASALT	BASALT	0.9744 CHERT 0.17 QUARTZITE 0.24
78	BASALT	BASALT	0.9329 CHERT 0.16 QUARTZITE 0.19
79	BASALT	QUARTZITE	0.5963 CHERT 0.20
80	BASALT	BASALT	0.7751 CHERT 0.11 QUARTZITE 0.11
81	BASALT	BASALT	0.7705 CHERT 0.21
82	BASALT	CHERT	0.4961 QUARTZITE 0.20
83	BASALT	BASALT	0.9514 CHERT 0.12 QUARTZITE 0.20
84	BASALT	BASALT	0.6407 CHERT 0.18 QUARTZITE 0.18
85	BASALT	BASALT	0.9888 CHERT 0.16
86	BASALT	BASALT	0.3956 CHERT 0.31 QUARTZITE 0.29
87	BASALT	BASALT	0.8950 CHERT 0.32
88	BASALT	BASALT	0.8954 CHERT 0.15 QUARTZITE 0.26
89	BASALT	BASALT	0.6790 CHERT 0.14 QUARTZITE 0.19
90	BASALT	BASALT	0.7374 CHERT 0.24
91	BASALT	BASALT	0.6997 CHERT 0.17 QUARTZITE 0.13
92	BASALT	BASALT	0.9437 QUARTZITE 0.28
93	BASALT	BASALT	0.9110 CHERT 0.16
94	BASALT	BASALT	0.8127 QUARTZITE 0.11
95	BASALT	BASALT	0.8613 CHERT 0.10
96	BASALT	BASALT	0.5964 CHERT 0.14 QUARTZITE 0.27
97	BASALT	BASALT	0.8789 CHERT 0.11 QUARTZITE 0.20

Row	Actual	Predicted	Prob Others (Pred)
98	BASALT	BASALT	0.6166 CHERT 0.29
99	BASALT	CHERT	0.5879 QUARTZITE 0.19
100	BASALT	BASALT	0.6503 CHERT 0.22 QUARTZITE 0.13
101	BASALT	QUARTZITE	0.4784 CHERT 0.21
102	BASALT	BASALT	0.7154 CHERT 0.19
103	BASALT	BASALT	0.7987 QUARTZITE 0.19
104	BASALT	QUARTZITE	0.7288 QUARTZITE 0.47
105	BASALT	BASALT	0.7945 QUARTZITE 0.19
106	BASALT	BASALT	0.7004 CHERT 0.12 QUARTZITE 0.18
107	BASALT	BASALT	0.5260 CHERT 0.45
108	BASALT	BASALT	0.5189 CHERT 0.46
109	BASALT	BASALT	0.6185 CHERT 0.37
110	BASALT	BASALT	0.9433 QUARTZITE 0.17
111	BASALT	QUARTZITE	0.5430 CHERT 0.17
112	BASALT	BASALT	0.7104 CHERT 0.15 QUARTZITE 0.14
113	BASALT	BASALT	0.8532 CHERT 0.14
114	BASALT	BASALT	0.5752 CHERT 0.29 QUARTZITE 0.14
115	BASALT	BASALT	0.6895 CHERT 0.16 QUARTZITE 0.16
116	BASALT	BASALT	0.5110 QUARTZITE 0.48
117	CHERT	CHERT	0.8251 BASALT 0.16
118	CHERT	CHERT	0.8646 BASALT 0.13
119	CHERT	BASALT	0.5572 QUARTZITE 0.10
120	CHERT	BASALT	0.6161 QUARTZITE 0.14
121	CHERT	BASALT	0.4493 QUARTZITE 0.18
122	CHERT	BASALT	0.9053 BASALT 0.31
123	CHERT	BASALT	0.8067 QUARTZITE 0.19
124	CHERT	QUARTZITE	0.5177 BASALT 0.32
125	CHERT	BASALT	0.5265
126	CHERT	CHERT	0.7471 BASALT 0.24
127	CHERT	CHERT	0.9927 QUARTZITE 0.12
128	CHERT	CHERT	0.9451 QUARTZITE 0.12
129	CHERT	BASALT	0.7642 QUARTZITE 0.35
130	CHERT	BASALT	0.5748 QUARTZITE 0.15
131	CHERT	BASALT	0.4750 QUARTZITE 0.15
132	CHERT	BASALT	0.4642 QUARTZITE 0.25
133	CHERT	BASALT	0.4134 QUARTZITE 0.37
134	CHERT	CHERT	0.4995 BASALT 0.36 QUARTZITE 0.14
135	CHERT	CHERT	0.9487 QUARTZITE 0.17
136	CHERT	CHERT	0.3517 BASALT 0.34 QUARTZITE 0.31
137	CHERT	CHERT	0.9367 BASALT 0.16
138	CHERT	CHERT	0.9923 QUARTZITE 0.12
139	CHERT	CHERT	0.4808 BASALT 0.47
140	CHERT	BASALT	0.6929 BASALT 0.31 QUARTZITE 0.27
141	CHERT	BASALT	0.3870 QUARTZITE 0.29
142	CHERT	CHERT	0.7887 BASALT 0.21
143	CHERT	BASALT	0.6283 QUARTZITE 0.14
144	CHERT	BASALT	0.5289 QUARTZITE 0.22
145	CHERT	BASALT	0.5815 BASALT 0.33 QUARTZITE 0.29
146	CHERT	CHERT	0.8497 BASALT 0.14
147	CHERT	BASALT	0.5649 QUARTZITE 0.22
148	CHERT	BASALT	0.6267 QUARTZITE 0.16
149	CHERT	BASALT	0.5886 QUARTZITE 0.16

Row	Actual	Predicted	Prob Others (Pred)
150	CHERT	CHERT	0.7217 BASALT 0.28
151	CHERT	CHERT	0.5332 BASALT 0.46
152	CHERT	BASALT	0.4902 QUARTZITE 0.24
153	CHERT	BASALT	0.5483 QUARTZITE 0.27
154	CHERT	BASALT	0.5636 QUARTZITE 0.20
155	CHERT	CHERT	0.6340 BASALT 0.35
156	CHERT	QUARTZITE	0.3958 BASALT 0.31
157	CHERT	CHERT	0.5140 BASALT 0.44
158	CHERT	BASALT	0.4657 QUARTZITE 0.25
159	CHERT	CHERT	0.6029 QUARTZITE 0.34
160	CHERT	QUARTZITE	0.5717 BASALT 0.13 QUARTZITE 0.39
161	CHERT	BASALT	0.5935 QUARTZITE 0.14
162	CHERT	CHERT	0.5655 BASALT 0.15 QUARTZITE 0.28
163	CHERT	CHERT	0.5635 QUARTZITE 0.38
164	CHERT	CHERT	0.7246 BASALT 0.20
165	CHERT	BASALT	0.4737 BASALT 0.28
166	BASALT	BASALT	0.5395 CHERT 0.25 QUARTZITE 0.21
167	BASALT	BASALT	0.7799 CHERT 0.12
168	BASALT	BASALT	0.8272 CHERT 0.12
169	BASALT	BASALT	0.6199 CHERT 0.33
170	BASALT	BASALT	0.4145 CHERT 0.24 QUARTZITE 0.35
171	BASALT	QUARTZITE	0.3386 CHERT 0.33
172	BASALT	BASALT	0.7809 CHERT 0.18
173	BASALT	BASALT	0.4583 CHERT 0.30 QUARTZITE 0.24
174	BASALT	BASALT	0.7467 CHERT 0.17
175	BASALT	BASALT	0.7419 CHERT 0.24
176	BASALT	BASALT	0.7968 CHERT 0.13
177	BASALT	BASALT	0.8069 CHERT 0.15 QUARTZITE 0.20
178	BASALT	BASALT	0.6174 CHERT 0.15 QUARTZITE 0.23
179	BASALT	BASALT	0.4949 QUARTZITE 0.42
180	BASALT	BASALT	0.6960 QUARTZITE 0.22
181	BASALT	BASALT	0.7186 CHERT 0.13 QUARTZITE 0.15
182	BASALT	BASALT	0.6829 CHERT 0.31
183	BASALT	QUARTZITE	0.4782 CHERT 0.23
184	BASALT	BASALT	0.4380 CHERT 0.42 QUARTZITE 0.14
185	BASALT	QUARTZITE	0.5061 CHERT 0.28
186	BASALT	CHERT	0.4704 CHERT 0.34
187	BASALT	BASALT	0.4357 CHERT 0.18 QUARTZITE 0.38
188	BASALT	BASALT	0.6878 CHERT 0.24
189	BASALT	BASALT	0.7691 QUARTZITE 0.21
190	BASALT	BASALT	0.5136 CHERT 0.40
191	BASALT	BASALT	0.6354 CHERT 0.30
192	BASALT	BASALT	0.6429 CHERT 0.35
193	BASALT	BASALT	0.6235 CHERT 0.20 QUARTZITE 0.17
194	BASALT	BASALT	0.5183 CHERT 0.14 QUARTZITE 0.34
195	BASALT	BASALT	0.8311 CHERT 0.33
196	BASALT	BASALT	0.6924 CHERT 0.16 QUARTZITE 0.15
197	BASALT	BASALT	0.8333 CHERT 0.15
198	BASALT	BASALT	0.8284 QUARTZITE 0.16
199	BASALT	BASALT	0.5925 CHERT 0.40
200	BASALT	QUARTZITE	0.5330 CHERT 0.33
201	BASALT	BASALT	0.4177 CHERT 0.34 QUARTZITE 0.24

Row	Actual	Predicted	Prob Others (Pred)
202	BASALT	BASALT	0.7817 CHERT 0.16
203	BASALT	BASALT	0.5524 CHERT 0.11 QUARTZITE 0.34
204	BASALT	BASALT	0.5067 CHERT 0.18 QUARTZITE 0.31
205	BASALT	BASALT	0.8130 CHERT 0.13
206	BASALT	BASALT	0.4033 CHERT 0.36 QUARTZITE 0.24
207	BASALT	BASALT	0.5137 CHERT 0.46
208	BASALT	BASALT	0.6270 CHERT 0.32
209	BASALT	BASALT	0.7055 QUARTZITE 0.28
210	BASALT	BASALT	0.6292 CHERT 0.37
211	BASALT	BASALT	0.6075 CHERT 0.12 QUARTZITE 0.27
212	BASALT	BASALT	0.6798 CHERT 0.16 QUARTZITE 0.16
213	CHERT	CHERT	0.8200 QUARTZITE 0.13
214	CHERT	CHERT	0.8866 QUARTZITE 0.10
215	CHERT	CHERT	0.9985 QUARTZITE 0.34
216	CHERT	CHERT	0.7645 BASALT 0.21
217	CHERT	CHERT	0.6653 QUARTZITE 0.25
218	CHERT	BASALT	0.3748 QUARTZITE 0.34
219	CHERT	CHERT	0.9839 QUARTZITE 0.40
220	CHERT	CHERT	0.9229 BASALT 0.11
221	CHERT	CHERT	0.8706 QUARTZITE 0.11
222	CHERT	CHERT	0.7237 QUARTZITE 0.25
223	CHERT	CHERT	0.9212 BASALT 0.21 QUARTZITE 0.30
224	CHERT	CHERT	0.9720 BASALT 0.14 QUARTZITE 0.23
225	CHERT	BASALT	0.7418 QUARTZITE 0.30
226	CHERT	BASALT	0.5550 QUARTZITE 0.28
227	CHERT	BASALT	0.7565 QUARTZITE 0.30
228	CHERT	QUARTZITE	0.5110 BASALT 0.20
229	CHERT	QUARTZITE	0.4881 BASALT 0.10
230	CHERT	BASALT	0.5765 QUARTZITE 0.35
231	CHERT	CHERT	0.8069 QUARTZITE 0.19
232	CHERT	CHERT	0.7699 QUARTZITE 0.23
233	CHERT	CHERT	1.0000
234	CHERT	CHERT	0.8919 QUARTZITE 0.10
235	CHERT	CHERT	0.7696 QUARTZITE 0.18
236	CHERT	CHERT	0.7996 QUARTZITE 0.15
237	CHERT	CHERT	0.7777 QUARTZITE 0.14
238	CHERT	BASALT	0.6293 BASALT 0.36 QUARTZITE 0.26
239	CHERT	BASALT	0.6744 QUARTZITE 0.29
240	CHERT	BASALT	0.6818 QUARTZITE 0.23
241	CHERT	CHERT	1.0000
242	CHERT	BASALT	0.5994 BASALT 0.28 QUARTZITE 0.26
243	CHERT	CHERT	0.6510 BASALT 0.30
244	CHERT	CHERT	0.6672 QUARTZITE 0.24
245	CHERT	CHERT	0.6829 BASALT 0.21 QUARTZITE 0.10
246	CHERT	CHERT	0.4633 BASALT 0.24 QUARTZITE 0.30
247	CHERT	CHERT	0.5400 BASALT 0.25 QUARTZITE 0.21
248	CHERT	CHERT	0.7791 BASALT 0.19
249	BASALT	BASALT	0.7535 CHERT 0.17
250	BASALT	CHERT	0.7602 QUARTZITE 0.34
251	BASALT	BASALT	0.9897 CHERT 0.20 QUARTZITE 0.33
252	BASALT	BASALT	0.5558 CHERT 0.21 QUARTZITE 0.23
253	BASALT	QUARTZITE	0.5473 QUARTZITE 0.35

Row	Actual	Predicted	Prob Others (Pred)
254	BASALT	BASALT	0.8743 CHERT 0.12
255	BASALT	BASALT	0.4419 CHERT 0.24 QUARTZITE 0.32
256	BASALT	BASALT	0.8664 CHERT 0.13
257	BASALT	CHERT	0.5194 QUARTZITE 0.21
258	BASALT	QUARTZITE	0.4212 CHERT 0.35
259	BASALT	BASALT	0.8587 QUARTZITE 0.14
260	CHERT	CHERT	0.8813 BASALT 0.12
261	BASALT	BASALT	0.7255 CHERT 0.25
262	BASALT	BASALT	0.9491 CHERT 0.21
263	BASALT	QUARTZITE	0.8537 QUARTZITE 0.19
264	BASALT	BASALT	0.8789 CHERT 0.12
265	BASALT	BASALT	0.5171 CHERT 0.47
266	BASALT	BASALT	0.7674 CHERT 0.23
267	CHERT	CHERT	0.9995 QUARTZITE 0.26
268	CHERT	CHERT	0.9996 QUARTZITE 0.25
269	QUARTZITE	BASALT	0.8570 BASALT 0.19 CHERT 0.39
270	BASALT	CHERT	0.9540 QUARTZITE 0.30
271	CHERT	CHERT	0.9804 BASALT 0.16
272	QUARTZITE	QUARTZITE	0.8536 BASALT 0.15
273	BASALT	BASALT	0.5994 QUARTZITE 0.38
274	CHERT	CHERT	0.9776 QUARTZITE 0.31
275	BASALT	CHERT	0.5529 QUARTZITE 0.16
276	BASALT	BASALT	0.9787 CHERT 0.12

'*' indicates misclassified
 "~" indicates excluded row

APPENDIX D – DISCRIMINANT SCORES OF THE QDA MODEL FOR TECHNOLOGY CLASSIFICATION

Row	Actual	SqDist (Actual)	Prob (Actual)	-Log Prob (Prob)	Predicted	Prob Others (Pred)
1	HEBT4_L7_232-1	.	.	.	NR	0.9992
2	HEBT4_L8_147-1	.	.	.	NR	0.9998
3	HEBT4_L8_223-1	.	.	.	BF	0.9524
4	HEBT4_L8_294-2	.	.	.	NR	0.6533 BF 0.35
5	HEBT4_L8_359-2	.	.	.	NR	0.9311
6	HEBT4_L8_359-2b	.	.	.	BF	0.8437 NR 0.16
7	HEBT4_L8_372-3a	.	.	.	NR	0.8639 BF 0.14
8	HEBT4_L8_372-3b	.	.	.	NR	0.9952
9	HEBT4_L8_373-2	.	.	.	BF	0.9001
10	HEBT4_L7_195-1	.	.	.	NR	0.8556 BF 0.14
11	HEBT4_L8_351-2	.	.	.	NR	1.0000
12	HEBT4_L8_372-4	.	.	.	NR	0.9999
13	HEBT4_L8_391-1	.	.	.	NR	0.9892
14	HEBT4_L8_359-1a	.	.	.	NR	0.9997
15	HEBT4_L8_188-1	.	.	.	NR	0.9960
16	HEBT4_L8_232-1	.	.	.	BF	0.6835 NR 0.32
17	HEBT4_L8_351-1	.	.	.	NR	0.9978
18	HEBT4_L8_372-1	.	.	.	NR	0.9538
19	HEBT4_L8_468-2	.	.	.	NR	0.9952
20	HEBT4_L8_359-1b	.	.	.	NR	1.0000
21	BF	-28.0366	0.9943	0.006	BF	0.9943
22	BF	-31.2941	0.7485	0.290	BF	0.7485 NR 0.25
23	BF	-26.6395	0.9045	0.100	BF	0.9045
24	BF	-32.0300	0.8710	0.138	BF	0.8710 NR 0.13
25	BF	-24.3211	0.7198	0.329	BF	0.7198 NR 0.28
26	BF	-32.0894	0.8417	0.172	BF	0.8417 NR 0.16
27	BF	-34.0628	0.9768	0.023	BF	0.9768
28	BF	-32.3026	0.0924	2.382	FLAKE	0.8825
29	BF	-28.9625	0.8921	0.114	BF	0.8921 NR 0.11
30	BF	-18.8561	0.8272	0.190	BF	0.8272 NR 0.17
31	BF	-23.3865	0.4503	0.798	NR	0.5497
32	BF	-31.6426	0.5735	0.556	BF	0.5735 NR 0.41
33	BF	-34.9046	0.4204	0.867	FLAKE	0.4910
34	BF	-30.4402	0.3669	1.003	NR	0.6331
35	BF	-22.0484	0.9733	0.027	BF	0.9733
36	BF	-30.8452	0.9504	0.051	BF	0.9504
37	BF	-33.4005	0.6654	0.407	BF	0.6654 NR 0.33
38	BF	-28.0851	0.9355	0.067	BF	0.9355
39	BF	-31.6544	0.8050	0.217	BF	0.8050 NR 0.16
40	BF	-33.1881	0.8980	0.108	BF	0.8980 NR 0.10
41	BF	-32.9398	0.2273	1.482	NR	0.7725
42	BF	-26.4572	0.3021	1.197	CORE	0.4795 NR 0.22
43	BF	-26.9311	0.9690	0.031	BF	0.9690
44	BF	-21.0075	0.0204	3.892	CORE	0.9514
45	NR	-32.0962	0.9770	0.023	NR	0.9770

Row	Actual	SqDist (Actual)	Prob (Actual)	-Log Predicted (Prob)	Prob Others (Pred)
46	NR	-23.8099	0.6608	0.414 NR	0.6608 BF 0.34
47	NR	-21.6870	0.5968	0.516 NR	0.5968 BF 0.40
48	NR	-12.2595	0.9806	0.020 NR	0.9806
49	NR	-21.4587	0.2435	1.413 BF	0.7565
50	NR	-11.9448	1.0000	0.000 NR	1.0000
51	NR	-11.8649	0.9999	0.000 NR	0.9999
52	NR	-23.5961	0.0415	3.181 BF	0.8140 CORE 0.14
53	NR	-20.9633	0.9506	0.051 NR	0.9506
54	NR	-18.1335	0.2382	1.435 BF	0.7444
55	NR	-30.8074	0.4115	0.888 BF	0.5885
56	NR	-34.5473	0.7517	0.285 NR	0.7517 BF 0.24
57	NR	-25.5223	0.9493	0.052 NR	0.9493
58	NR	-26.0888	0.0521	2.954 BF	0.9477
59	NR	-31.4385	0.9918	0.008 NR	0.9918
60	NR	-31.2873	0.8703	0.139 NR	0.8703 BF 0.13
61	NR	-34.7316	0.8380	0.177 NR	0.8380 BF 0.16
62	NR	-33.8454	0.8117	0.209 NR	0.8117 BF 0.19
63	NR	-30.6375	0.8553	0.156 NR	0.8553 BF 0.14
64	NR	-28.3342	0.5457	0.606 NR	0.5457 BF 0.45
65	NR	42.7756	0.0000	12.503 CORE	0.9961
66	NR	-35.9751	0.4488	0.801 BF	0.5497
67	NR	-32.4785	0.4698	0.755 BF	0.5202
68	NR	-32.9285	0.8647	0.145 NR	0.8647 BF 0.14
69	BF	-31.6993	0.8610	0.150 BF	0.8610 NR 0.14
70	BF	-23.0524	0.9321	0.070 BF	0.9321
71	BF	-31.1723	0.7860	0.241 BF	0.7860 NR 0.21
72	BF	-33.0252	0.5681	0.566 BF	0.5681 NR 0.43
73	BF	-29.2910	0.8625	0.148 BF	0.8625 NR 0.14
74	BF	-24.2048	0.6375	0.450 BF	0.6375 NR 0.36
75	BF	-34.0783	0.8091	0.212 BF	0.8091 NR 0.19
76	BF	-36.6676	0.5654	0.570 BF	0.5654 NR 0.43
77	BF	-23.7537	0.7422	0.298 BF	0.7422 NR 0.26
78	BF	-31.2248	0.7903	0.235 BF	0.7903 NR 0.21
79	BF	-9.9458	0.0031	5.762 NR	0.9969
80	BF	-31.7936	0.7932	0.232 BF	0.7932 NR 0.21
81	BF	-28.4383	0.7994	0.224 BF	0.7994 NR 0.20
82	BF	-29.8722	0.9369	0.065 BF	0.9369
83	BF	-12.4378	0.8439	0.170 BF	0.8439 NR 0.16
84	BF	-34.0759	0.6743	0.394 BF	0.6743 NR 0.33
85	BF	-12.2859	0.2046	1.586 NR	0.7954
86	BF	-33.8764	0.9010	0.104 BF	0.9010
87	BF	-24.9508	0.5858	0.535 BF	0.5858 NR 0.41
88	BF	-32.8391	0.8048	0.217 BF	0.8048 NR 0.20
89	BF	-29.3327	0.2641	1.332 NR	0.7359
90	BF	-29.2687	0.6240	0.472 BF	0.6240 NR 0.38
91	BF	-23.7819	0.8793	0.129 BF	0.8793 NR 0.12
92	BF	-15.7913	0.6700	0.401 BF	0.6700 NR 0.33
93	NR	-26.8911	0.7408	0.300 NR	0.7408 BF 0.26
94	NR	-27.3595	0.9509	0.050 NR	0.9509
95	NR	-30.0014	0.9351	0.067 NR	0.9351
96	NR	-29.9535	0.4744	0.746 BF	0.5256
97	NR	-18.3195	0.5087	0.676 NR	0.5087 BF 0.49

Row	Actual	SqDist (Actual)	Prob (Actual)	-Log Predicted (Prob)	Prob Others (Pred)
98	NR	-31.7087	0.8963	0.109 NR	0.8963 BF 0.10
99	NR	-26.4541	0.8182	0.201 NR	0.8182 BF 0.18
100	NR	-34.6955	0.8649	0.145 NR	0.8649 BF 0.14
101	NR	-30.7602	0.9748	0.026 NR	0.9748
102	NR	-24.2919	0.0336	3.392 BF	0.9664
103	NR	-22.8731	0.5636	0.573 NR	0.5636 BF 0.44
104	NR	-24.7150	0.9088	0.096 NR	0.9088
105	NR	-28.5945	0.9417	0.060 NR	0.9417
106	NR	-32.6661	0.7017	0.354 NR	0.7017 BF 0.30
107	NR	-26.2730	0.7195	0.329 NR	0.7195 BF 0.25
108	NR	-30.1303	0.7577	0.278 NR	0.7577 BF 0.24
109	NR	-30.3579	0.8749	0.134 NR	0.8749 BF 0.13
110	NR	-26.4764	0.9943	0.006 NR	0.9943
111	NR	-33.2915	0.9469	0.055 NR	0.9469
112	NR	-35.3393	0.9537	0.047 NR	0.9537
113	NR	-14.9523	0.5807	0.543 NR	0.5807 BF 0.42
114	NR	-34.1460	0.9653	0.035 NR	0.9653
115	NR	-31.3962	0.9970	0.003 NR	0.9970
116	NR	-15.7784	0.9999	0.000 NR	0.9999
117	BF	-25.6082	0.3104	1.170 NR	0.6896
118	BF	-21.8648	0.6448	0.439 BF	0.6448 NR 0.36
119	BF	-29.9007	0.7532	0.283 BF	0.7532 NR 0.25
120	BF	-36.2649	0.7102	0.342 BF	0.7102 NR 0.29
121	BF	-29.9087	0.2520	1.378 NR	0.7470
122	BF	-12.1365	0.8528	0.159 BF	0.8528 NR 0.15
123	BF	-34.6586	0.4901	0.713 NR	0.5099
124	BF	-28.2108	0.3485	1.054 NR	0.6514
125	BF	-22.1327	0.9150	0.089 BF	0.9150
126	BF	-15.6838	0.5245	0.645 BF	0.5245 NR 0.48
127	BF	-22.5062	0.8972	0.108 BF	0.8972 NR 0.10
128	BF	-20.1201	0.9750	0.025 BF	0.9750
129	BF	-27.8989	0.1229	2.096 NR	0.8770
130	BF	-33.8064	0.6411	0.445 BF	0.6411 NR 0.36
131	BF	-33.3227	0.4022	0.911 NR	0.5300
132	BF	-35.1206	0.3990	0.919 NR	0.6010
133	BF	-29.0556	0.5083	0.677 BF	0.5083 NR 0.49
134	BF	-31.9108	0.8521	0.160 BF	0.8521 NR 0.15
135	BF	-18.3116	0.8388	0.176 BF	0.8388 NR 0.16
136	BF	-30.9807	0.5091	0.675 BF	0.5091 NR 0.49
137	BF	-16.9849	0.6398	0.447 BF	0.6398 NR 0.36
138	BF	-3.1806	1.0000	0.000 BF	1.0000
139	BF	-31.6270	0.7309	0.314 BF	0.7309 NR 0.27
140	NR	-22.0427	0.9936	0.006 NR	0.9936
141	NR	-24.7469	0.6310	0.460 NR	0.6310 BF 0.37
142	NR	-21.6403	0.4706	0.754 BF	0.5294
143	NR	-30.5360	0.4889	0.716 BF	0.5008
144	NR	-35.9805	0.5757	0.552 NR	0.5757 BF 0.42
145	NR	-32.3518	0.5030	0.687 NR	0.5030 BF 0.50
146	NR	-18.2195	0.2919	1.231 BF	0.7081
147	NR	-35.6383	0.9110	0.093 NR	0.9110
148	NR	-32.2305	0.9423	0.059 NR	0.9423
149	NR	-34.4448	0.0452	3.097 FLAKE	0.8475 BF 0.11

Row	Actual	SqDist (Actual)	Prob (Actual)	-Log Predicted (Prob)	Prob Others (Pred)
150	NR	-17.1836	0.9315	0.071 NR	0.9315
151	NR	-25.4541	0.9819	0.018 NR	0.9819
152	NR	-32.7159	0.8842	0.123 NR	0.8842 BF 0.12
153	NR	-31.7997	0.9483	0.053 NR	0.9483
154	NR	-29.7446	0.2720	1.302 BF	0.7280
155	NR	-26.8152	0.0885	2.425 BF	0.9115
156	NR	-28.3488	0.5411	0.614 NR	0.5411 BF 0.46
157	NR	-28.4616	0.3633	1.012 BF	0.6367
158	NR	-28.4390	0.9967	0.003 NR	0.9967
159	NR	-25.2872	0.9690	0.031 NR	0.9690
160	NR	-29.7830	0.9987	0.001 NR	0.9987
161	NR	-28.0959	0.8341	0.181 NR	0.8341 BF 0.17
162	NR	-30.1809	0.9760	0.024 NR	0.9760
163	NR	-29.7529	0.9235	0.080 NR	0.9235
164	NR	-28.9518	0.9863	0.014 NR	0.9863
165	NR	-33.5485	0.7196	0.329 NR	0.7196 BF 0.28
166	BF	-32.8319	0.4925	0.708 NR	0.5075
167	BF	-33.5969	0.3552	1.035 NR	0.6448
168	BF	-26.0957	0.5509	0.596 BF	0.5509 NR 0.45
169	BF	-33.3645	0.8523	0.160 BF	0.8523 NR 0.12
170	BF	-25.0216	0.3685	0.998 NR	0.6315
171	BF	-31.8817	0.3256	1.122 NR	0.6744
172	BF	-29.6930	0.4049	0.904 NR	0.5833
173	BF	-36.4816	0.6004	0.510 BF	0.6004 FLAKE 0.26 NR 0.14
174	BF	-33.1578	0.8857	0.121 BF	0.8857 NR 0.11
175	BF	-31.9649	0.4422	0.816 BF	0.4422 FLAKE 0.30 NR 0.26
176	BF	-27.8609	0.3578	1.028 NR	0.6422
177	BF	-34.9184	0.4770	0.740 NR	0.5229
178	BF	-31.8172	0.7667	0.266 BF	0.7667 NR 0.23
179	BF	-33.4903	0.3856	0.953 NR	0.6144
180	BF	-29.5808	0.8581	0.153 BF	0.8581 NR 0.14
181	BF	-32.4880	0.4037	0.907 NR	0.5963
182	BF	-20.8381	0.7409	0.300 BF	0.7409 NR 0.26
183	BF	-33.5140	0.8541	0.158 BF	0.8541 NR 0.12
184	BF	-33.0825	0.7419	0.298 BF	0.7419 FLAKE 0.23
185	BF	-26.3758	0.8322	0.184 BF	0.8322 NR 0.17
186	BF	-27.6851	0.9473	0.054 BF	0.9473
187	BF	-33.5230	0.4528	0.792 NR	0.5472
188	BF	-32.7322	0.9755	0.025 BF	0.9755
189	NR	-28.0191	0.9925	0.008 NR	0.9925
190	NR	-29.5253	0.7304	0.314 NR	0.7304 BF 0.27
191	NR	-32.8746	0.7450	0.294 NR	0.7450 BF 0.26
192	NR	-31.6720	0.6523	0.427 NR	0.6523 BF 0.35
193	NR	-29.5825	0.3087	1.175 BF	0.6913
194	NR	-31.5654	0.7494	0.288 NR	0.7494 BF 0.25
195	NR	-31.1712	0.9569	0.044 NR	0.9569
196	NR	-21.9996	0.8964	0.109 NR	0.8964 BF 0.10
197	NR	-26.5458	0.2530	1.374 BF	0.7451
198	NR	-27.9649	0.4481	0.803 BF	0.5519
199	NR	-22.2938	0.9973	0.003 NR	0.9973
200	NR	-29.8568	0.9547	0.046 NR	0.9547
201	NR	-30.3805	0.1854	1.685 BF	0.8146

Row	Actual	SqDist (Actual)	Prob (Actual)	-Log Predicted (Prob)	Prob Others (Pred)
202	NR	-30.8852	0.9314	0.071 NR	0.9314
203	NR	-31.1900	0.9868	0.013 NR	0.9868
204	NR	-32.5987	0.8807	0.127 NR	0.8807 BF 0.12
205	NR	-32.3512	0.8337	0.182 NR	0.8337 BF 0.17
206	NR	-28.3835	0.6747	0.394 NR	0.6747 BF 0.33
207	NR	-30.0274	0.7661	0.266 NR	0.7661 BF 0.23
208	NR	-35.5909	0.7469	0.292 NR	0.7469 BF 0.25
209	NR	-25.5543	0.6869	0.376 NR	0.6869 BF 0.31
210	NR	-21.1819	0.6982	0.359 NR	0.6982 BF 0.29
211	NR	-33.8789	0.5065	0.680 NR	0.5065 BF 0.20 CORE 0.29
212	NR	-24.3939	0.9089	0.095 NR	0.9089
213	BF	-14.9380	0.9175	0.086 BF	0.9175
214	BF	-29.9253	0.9992	0.001 BF	0.9992
215	BF	-25.7183	0.5959	0.518 BF	0.5959 FLAKE 0.40
216	BF	-27.5014	0.9730	0.027 BF	0.9730
217	BF	-31.2025	0.4871	0.719 BF	0.4871 CORE 0.27 FLAKE 0.19
218	BF	-33.3251	0.9391	0.063 BF	0.9391
219	BF	-19.6799	0.7320	0.312 BF	0.7320 FLAKE 0.27
220	BF	-26.5189	0.0943	2.361 FLAKE	0.8700
221	BF	-32.4979	0.6924	0.368 BF	0.6924 FLAKE 0.31
222	BF	-32.5746	0.9932	0.007 BF	0.9932
223	BF	-25.7014	0.9954	0.005 BF	0.9954
224	BF	-31.9144	0.8604	0.150 BF	0.8604 FLAKE 0.14
225	BF	-31.7825	0.9407	0.061 BF	0.9407
226	BF	-24.2823	0.4432	0.814 NR	0.5568
227	BF	-27.4324	0.2896	1.239 NR	0.7104
228	BF	-17.8358	0.9483	0.053 BF	0.9483
229	BF	-29.0485	0.9856	0.015 BF	0.9856
230	BF	-19.8017	0.4821	0.730 NR	0.5179
231	FLAKE	-32.1892	0.9993	0.001 FLAKE	0.9993
232	FLAKE	-38.3809	0.9989	0.001 FLAKE	0.9989
233	FLAKE	-29.4441	1.0000	0.000 FLAKE	1.0000
234	FLAKE	-34.5001	0.9683	0.032 FLAKE	0.9683
235	FLAKE	-41.6398	0.9977	0.002 FLAKE	0.9977
236	FLAKE	-35.5175	0.9924	0.008 FLAKE	0.9924
237	FLAKE	-40.7806	0.9973	0.003 FLAKE	0.9973
238	FLAKE	-40.6438	0.9043	0.101 FLAKE	0.9043
239	FLAKE	-33.7141	0.9069	0.098 FLAKE	0.9069
240	FLAKE	-34.7138	0.5657	0.570 FLAKE	0.5657 BF 0.13 NR 0.31
241	FLAKE	-29.7360	1.0000	0.000 FLAKE	1.0000
242	FLAKE	-35.3414	0.4391	0.823 FLAKE	0.4391 BF 0.25 NR 0.31
243	FLAKE	-29.8885	0.1210	2.112 BF	0.7245 NR 0.15
244	FLAKE	-37.4309	0.7379	0.304 FLAKE	0.7379 BF 0.25
245	FLAKE	-36.3756	0.9687	0.032 FLAKE	0.9687
246	FLAKE	-35.8501	0.4759	0.743 FLAKE	0.4759 BF 0.36 NR 0.16
247	FLAKE	-35.8073	0.5210	0.652 FLAKE	0.5210 BF 0.43
248	FLAKE	-32.9383	0.9437	0.058 FLAKE	0.9437
249	CORE	-38.4965	0.9740	0.026 CORE	0.9740
250	CORE	-31.6805	0.7499	0.288 CORE	0.7499 BF 0.22
251	CORE	-32.8253	0.9997	0.000 CORE	0.9997
252	CORE	-32.1466	0.9195	0.084 CORE	0.9195
253	CORE	-31.8310	0.9986	0.001 CORE	0.9986

Row	Actual	SqDist (Actual)	Prob (Actual)	-Log Predicted (Prob)	Prob Others (Pred)
254	CORE	-31.6388	0.9320	0.070 CORE	0.9320
255	CORE	-31.9670	0.3748	0.981 BF	0.5315
256	CORE	-31.8829	0.9931	0.007 CORE	0.9931
257	CORE	-32.5843	0.6734	0.395 CORE	0.6734 BF 0.31
258	CORE	-31.7643	0.1342	2.009 BF	0.5424 NR 0.30
259	CORE	-32.1405	0.9997	0.000 CORE	0.9997
260	BF	-12.2097	1.0000	0.000 BF	1.0000
261	BF	-25.5072	0.8640	0.146 BF	0.8640 NR 0.14
262	BF	-24.2212	0.5059	0.681 BF	0.5059 NR 0.49
263	CORE	-31.6457	1.0000	0.000 CORE	1.0000
264	NR	-11.3927	0.9923	0.008 NR	0.9923
265	BF	-7.7533	0.9781	0.022 BF	0.9781
266	NR	-8.8790	0.4103	0.891 BF	0.5897
267	BF	-12.8129	1.0000	0.000 BF	1.0000
268	BF	-9.2040	1.0000	0.000 BF	1.0000
269	NR	-21.6777	0.9993	0.001 NR	0.9993
270	NR	-16.1922	0.9994	0.001 NR	0.9994
271	BF	-12.6368	0.1852	1.686 NR	0.8148
272	BF	-18.5976	0.1279	2.056 CORE	0.8687
273	NR	-25.7948	0.9996	0.000 NR	0.9996
274	FLAKE	-32.2796	0.9988	0.001 FLAKE	0.9988
275	BF	-11.7618	0.9994	0.001 BF	0.9994
276	BF	5.0768	0.9999	0.000 BF	0.9999

'*' indicates misclassified

"~" indicates excluded row